# DEVELOPMENT OF AN EFFICIENT PLANNED MAINTENANCE FRAMEWORK FOR MARINE AND OFFSHORE MACHINERY OPERATING UNDER HIGHLY UNCERTAIN ENVIRONMENT

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A thesis submitted in partial fulfilment of the requirements of Liverpool John Moores University for the degree of Doctor of Philosophy

November 2017

# Declaration

*"I hereby declare that this thesis submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person, nor material which has been accepted for the award of any other degree or diploma of the university or other institutions of higher learning, except where due acknowledgement has been made in the text".*

**Maurice Asuquo/2017**

Signature: ………………………………. Date: ……………………….……..

# Dedication

This thesis is dedicated to my beloved wife Mary and my magnificent, blessed and lovely children Inyeneobong, Edidiong, EkeminiAbasi and Idaraobong for their prayers and supports throughout the period of my study. I admire their patience, tolerance and willingness to support me, which gave me encouragement to focus and complete my studies in parallel to my full-time job.

# Acknowledgements

The completion of this study has been made possible by the enormous support and contributions of many people and organisations that I would like to convey my appreciation and sincere gratitude to them in my acknowledgement.

Firstly, I am extremely appreciative to the Almighty God my creator for giving me the profound wisdom, strength, understanding, and opportunity to commence and complete such a challenging and life-changing project; to my parents, Chief Patrick Umoh and Mrs Angela Effiong for their prayers and well wishes; and to my house care fellowship members for their untiring prayers and encouragement.

I would like to thank my principal supervisor Professor Jin Wang, not only for his guidance, supervision and encouragement while completing this research, but also for believing in me and deciding to step in as my principal supervisor when Dr. Ramin Riahi who was my principal supervisor left the University. More importantly, Professor Wang's strong views on high quality research and deliverables have greatly encouraged me. It has been an honour and a pleasure to have worked with him as his sparkling ideas and innovative thinking in research are instrumental to the development of the methodological frameworks and structure of this thesis.

My deep admiration and gratitude goes to my co-supervisors Dr Ramin Riahi, Dr Geraint Phylip-Jones and Dr Lihong Zhang for their constructive comments, stimulating suggestions and advice, and constant encouragements. Special thanks to Mark Raynes (Shell Global Lubricants), Mirja Hasan and Damir Blazina (Shell Marine Products), Kevin Davies (IPU Group), and Francis Raynes (MAINTEC Engineering), for providing data and other necessary information for my research. I wish to also extend special thanks to all my friends especially Dr Uwem Udo and Dr Andrew John, and my colleagues in the research group Liverpool LOgistics Offshore and Marine (LOOM) Research Institute, Dr Ademola Ishola, Dr Ambisire Usman, Shamsudeen Hassan and Kumudthaa Muniandy for their supports and friendship.

Finally, my sincere appreciation to my siblings and my House Fellowship Brethren for their encouragement, supports and constant prayers.

# Abstract

The constantly increasing complexity of marine and offshore machinery is a consequence of a constant improvement in ship powering, automation, specialisation in cargo transport, new ship types, as well as an effort to make the sea transport more economic. Therefore, the criteria of reliability, availability and maintainability have become very important factors in the process of marine machinery design, operation and maintenance.

An important finding from the literature exposed that failure to marine machinery can cause both direct and indirect economic damage with a long-term financial consequence. Notably, many cases of machinery failures reported in databases were as a result of near misses and incidents which are potential accident indicators. Moreover, experience has shown that modelling of past accident events and scenarios can provide insights into how a machinery failure can be subsisted even if it is not avoidable, also a basis for risk analysis of the machinery in order to reveal its vulnerabilities. This research investigates the following modelling approach in order to improve the efficiency of marine and offshore machinery operating under highly uncertain environment.

Firstly, this study makes full use of evidential reasoning*'s* advantage to propose a novel fuzzy evidential reasoning sensitivity analysis method *(FER-SAM)* to facilitate the assessment of operational uncertainties (trend analysis, family analysis, environmental analysis, design analysis, and human reliability analysis) in ship cranes.

Secondly, a fuzzy rule based sensitivity analysis methodology is proposed as a maintenance prediction model for oil-wetted gearbox and bearing with emphasis on ship cranes by formulating a fuzzy logic box (diagnostic table), which provides the ship crane operators with a means to predict possible impending failure without having to dismantle the crane.

Thirdly, experience has shown that it is not financially possible to employ all the suggested maintenance strategies in the literature. Thus, this study proposed a fuzzy TOPSIS approach that can help the maintenance engineers to select appropriate strategies aimed at enhancing the performance of the marine and offshore machinery.

Finally, the developed models are integrated in order to facilitate a generic planned maintenance framework for robust improvement and management, especially in situations where conventional planned maintenance techniques cannot be implemented with confidence due to data deficiency.

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# Abbreviations

| | |
|---|---|
| AHP | Analytical Hierarchy Process |
| AIS | Automatic Identification System |
| ASTM | American Society for Testing and Materials |
| BDM | Belief Degree Matrix |
| BN | Bayesian Network |
| BPN | Bayesian Probability Network |
| CBM | Condition Based Maintenance |
| CM | Condition Monitoring |
| CMA | Condition Monitoring Approach |
| COC | Certificate of Competency |
| CR | Consistency Ratio |
| CRS | Crane Reliability Survey |
| DM | Decision Maker |
| DMP | Data Mining Process |
| DRGW | Denver, Rio Grande and Western Railway |
| D-S | Dempster-Shafer |
| ECM | Effective Centred Maintenance |
| ELECTRE | Elimination and Choice Expressing Reality |
| EMM | Effective Maintenance Modelling |
| ER | Evidential Reasoning |
| FAHP | Fuzzy Analytical Hierarchy Processing |
| FER | Fuzzy Evidential Reasoning |
| FER-SAM | Fuzzy Evidential Reasoning Sensitivity Analysis Model |
| FL | Fuzzy Logic |
| FMADM | Fuzzy Multiple Attribute Decision Making |
| FMECA | Failure Mode, Effects and Criticality Analysis |
| FNIS | Fuzzy Negative Ideal Solution |
| FPIS | Fuzzy Positive Ideal Solution |
| FPSO | Floating Production Storage and Offloading |
| FRB | Fuzzy Rule Base |
| FRB-SAM | Fuzzy Rule Base Sensitivity Analysis Model |
| FRA | Fuzzy Risk Assessment |
| FSA | Formal Safety Assessment |

| | |
|---|---|
| FSM | Fuzzy Set Modelling |
| FST | Fuzzy Set Theory |
| FTOPSIS | Fuzzy Technique for Order Preference by Similarity to Ideal Solution |
| GMM | Geometric Mean Method |
| HAZOPs | Hazard and Operability Studies |
| IMO | International Maritime Organisation |
| ISIC | International Standard Industrial Classification |
| ISO | International Organisation for Standardization |
| MADM | Multiple Attribute Decision Making |
| MAGDM | Multiple Attribute Group Decision Making |
| MAIB | Marine Accident Investigation Branch |
| MCDA | Multiple Criteria Decision Analysis |
| MCDM | Multiple Criteria Decision Making |
| MFs | Membership Functions |
| MMIS | Maintenance Management Information System |
| NACE | Statistical Classification of Economic Activities in the European Community |
| NIRP | Negative Ideal Reference Point |
| PLB | Predictive Logic Box |
| PIRP | Positive Ideal Reference Point |
| PM | Preventive Maintenance |
| PMS | Planned Maintenance System |
| PRA | Probabilistic Risk Assessment |
| PROMETHEE | Preference Ranking Organisation Method for Enriching Evaluation |
| QDT | Quantitative Data Transformation |
| QRA | Quantitative Risk Assessment or Qualitative Risk Assessment |
| QSMS | Quality and Safety Management System |
| RCM | Reliability Centred Maintenance |
| SCR | Ship Crane Reliability |
| STCW | Standards of Training, Certifications & Watch-keeping |
| TFN | Triangular Fuzzy Number |
| TOPSIS | Technique for Order Preference by Similarity to Ideal Solution |
| TPM | Total Productive Maintenance |
| WAM | Weighted Arithmetic Mean |
| ZFN | Trapezoidal Fuzzy Number |

# Chapter 1

# Introduction

**Summary**

This chapter introduces the background of the research, and in doing so highlights the problems faced by monitoring the condition of marine and offshore machinery operating in an uncertain environment. The research objectives and hypothesis are also highlighted. They set out a logical platform aimed at addressing the outlined problems. There is an ever-increasing need for improving efficiency, reducing costs and increasing safety and reliability, each intrinsically linked with one another. The main research methodology is briefly described along with the scope and structure of the research.

## 1.1 Research Background

The marine and offshore industry today exists in a competitive market, which is a complex entity to examine for several reasons. Firstly, the industry has no nomenclature of economic activities (NACE) code, which therefore makes it difficult to define the sector (Olesen, 2016). NACE is the European statistical classification of economic activities which groups organizations according to their business activities. Statistics produced based on NACE are comparable at European level and, in general, at world level, in line with the United Nations' International Standard Industrial Classification (ISIC). Secondly, the industry consists of a multitude of different markets with different value chains. For example, the turbine installation company operates in a market that is very different from the market of the pump manufacturer or the supplier of safety equipment, although they are all part of the marine and offshore sector. Thirdly, the importance of the marine and offshore sector varies between the different actors. For instance, the drilling contractor is totally dependent on the offshore sector, but for the pump manufacturer, however, the offshore sector may only account for a smaller part of the total turnover.

Marine and offshore machinery are susceptible to diverse failures in their challenging field of operations due to their interactions and interdependence often associated with a high level of uncertainty. The alarming increase in cost, maintenance complications, and their effect on operation has prompted a need for effective maintenance planning, management and supervision of the maintenance process.

The maintenance of marine and offshore machinery increasingly involves a large number of engineering services and supplier companies. Thus, there is strong competition among suppliers to provide the best services to the operators. In order for services and supplier companies to win contracts, they must be able to quickly react to manufacturers' requirements and provide high quality and innovative solutions in a timely manner. It is also essential for them to develop and deliver planned maintenance systems as efficiently as possible.

Maintenance is an integral part of the marine and offshore industry, with a successful maintenance strategy delivering improvements to a company through increased productivity and efficiency whilst reducing the associated costs. The main aim of maintenance is threefold. Firstly, the equipment or system must have the highest possible reliability. Secondly, the downtime of equipment must be minimal. Thirdly, maintenance costs should be minimised (Bousdekis *et al*., 2016). As alluded by Bengtsson and Kurdve (2016), the total cost of maintenance is extremely difficult to calculate because of the number of factors which are affected when a machine or a piece of equipment fails. Typical factors may include: disruption to productivity, loss of productivity, downtime of failed equipment, quality of a product, inefficient use of personnel, repair time and repair costs. It is therefore essential to have an effective maintenance strategy in place in order to remain competitive.

Effective maintenance modelling (EMM) can deliver greater efficiency in the form of reductions in downtime of equipment, optimisation of inspection intervals, and reduced downtime for inspections, with each improvement bringing about its own reductions in costs to the business. EMM provides an informed and cost-effective basis to assist firms in decision-making and a means to keep system performance at a desired level. As such, research on maintenance modelling has attracted considerable attention. However, in the case of a company producing a product which is considered harmful to the environment, should failure take place, the prevention of failures becomes vital to the company. However, the inspection interval is often devised through subjective means (i.e. discussions with maintenance personnel). Andrews and Moss (2002) claim that maintenance is often performed for years without consideration to costs relating to inspection, breakdowns or downtime of equipment. Meanwhile, the advanced tools and techniques, which may be used for streamlining, updating and assessing current methods, are either unknown or inefficiently applied to a maintenance department. This may be down to a lack of knowledge, insufficient time allowed to study problems or situations, failure to understand modern techniques available, or limited knowledge within the company.

There are several maintenance concepts and tools that enable equipment, machines or processes to be maintained in a cost effective manner whilst minimising downtime and maximising reliability. Such concepts and tools include Reliability Centred Maintenance (RCM) (Tang *et al.*, 2016), Preventative Maintenance (PM), Condition-Based Maintenance (CBM) or Predictive Maintenance, and Total Productive Maintenance (TPM) (Borris, 2006). However, they must be utilised in an effective manner, and often, adopting several of these methods in combination helps to achieve cost effective results (Pillay and Wang, 2003).

Toms and Toms (2008) claim that the increasing corporate support and improved analytical procedures have paved the way for condition-based maintenance (CBM) which became predominant in the railway industry during the 1980s. However, this is not the case in the maritime industry as CBM is still a subject of debate in certain areas of maritime operations due to its inability to meet operators' satisfactions. Mills (2012) defines CBM as a maintenance strategy whereby symptoms and parameters are measured to detect and monitor potential faults. CBM enables maintenance to be carried out only when it is indicated to be necessary, rather than at fixed intervals. It is also known as predictive maintenance or condition monitoring, and it is covered in a range of ISO Standards. Condition monitoring techniques include:

- Vibration Monitoring
- Infra-red Thermography
- Acoustic Emission
- Ultrasonic
- Tribology and Lubrication (Oil Condition Monitoring)

Applying modelling techniques such as evidential reasoning (ER) (Liu *et al.,* 2015), (Zhang *et al.,* 2015), (Dymova and Sevastjanov, 2014), (Liu *et al.,* 2011), (Xu and Yang, 2005) and rule-base (Ramezani and Memariani, 2011), (Liu *et al.*, 2005) to complex systems can be valuable. These techniques, given certain parameters, can establish an inspection interval based on minimising downtime or reducing inspection costs. There are several examples for applying planned maintenance strategies in machinery components such as bearing in pumps (Woodard and Wolka, 2011), slewing bearing in ship cranes (Rezmireş *et al.,* 2010), (LYC, 2006), gearboxes in domestic wastewater pumps (Tiffany, 2014), winches on fishing vessels (Pillay and Wang, 2003a) and hydraulic systems in rotary drilling machines (Rahimdel *et al.*, 2013). At present though, no research has been carried out applying such modelling techniques to an environmentally hazardous industry, taking into account trend analysis, family analysis, human reliability analysis, design analysis, and environmental impact analysis should failure occur.

## 1.2 Statement of Problem

Most of the planned maintenance systems available fail to measure the reliability of the machinery with respect to trend analysis, family analysis, design analysis, environmental analysis, and the human errors common in marine and offshore operations. The challenge of this research is to extract the required information, from objective and subjective sources, in order to produce an effective planned maintenance methodology. The process of gathering data, the use of existing data or reliance on expert judgement has shown to be a troublesome process in terms of accuracy (Black *et al.,* 2003), (Pillay and Wang, 2003b).

The gathering of objective data in order to apply a modelling technique can be difficult, as it generally requires many months or even years to attain sufficient data (Aggarwal, 2015). The use of subjective data gathered from expert judgement can often come in a form which requires standardisation with existing data in order to establish consistency of data and ensure confidence in the modelling results. The combination of both objective and subjective data requires elicitation in order to establish the data, which is required to apply advanced modelling techniques to a marine and offshore company's maintenance management programme.

The risk of major failures in marine and offshore machinery is an area that is not thoroughly described in academic literature, and it is clear that complexity of the machinery stems from the interaction of their dependencies and the high levels of uncertainty in their operations. Moreover, complexity in the system often results in lack of visibility to monitor the safety performance of operations, as the analysts may have no detailed knowledge about the other part of the system. As a result of this, the analyst is unable to understand the optimisation measures required to enable the machinery to cope with unforeseen extortions and hazards, and maintain functionality of their operations to an acceptable level of performance.

Obviously, uncertainty associated with the marine and offshore machinery's operations makes it extremely difficult to clearly identify the vulnerability of the machinery in order to assess their risks. The interactive dependence of the machinery could significantly reduce the effectiveness of any maintenance strategies. However, in order to achieve reasonable safety and reliability, maintain cost-effectiveness and stay competitive, risk dependence of the machinery has to be accounted for when carrying out a collaborative modelling of the planned maintenance system for machinery management.

## 1.3 Research Aim and Objectives

The primary aim of this research is to propose a risk-based and decision-based planned maintenance methodology capable of delivering a maintenance strategy in the marine and offshore industry, to enable operators to move from current maintenance programme to a more efficient condition-based maintenance platform. This will lead to the enhancement of safety and sustainability of the marine and offshore machinery and transportation systems. The modelling of an advanced decision-based framework is a vital part of this thesis as it sets the foundation of the whole project. The planned maintenance methodology will serve to establish inspection intervals based on reducing downtime, reducing costs or understanding the risks relating to trend analysis, family analysis, design analysis, human reliability analysis and environmental analysis. In order to achieve this aim, this thesis outlines five objectives:

1. Investigation into the machinery and available planned maintenance programmes in the marine and offshore industries to identify key machinery system uncertainties and model failure risks associated with their operations.
2. Development of an integrated condition monitoring methodology to predict the condition of marine and offshore machinery operating under highly uncertain environment. This will be achieved in Chapter 4 utilising fuzzy set theory with evidential reasoning and analytical hierarchy process algorithms.
3. Development of a novel risk assessment model capable of predicting the risk levels of machinery components based on their laboratory oil sampling reports. This will achieved in Chapter 5 using the concept of belief degree and fuzzy rule-based theory.
4. Application of a multiple-attribute, group decision-making (MAGDM) model to select the best maintenance strategy for marine and offshore machinery. This will be achieved in Chapter 6 using based on a fuzzy techniques for order preference by similarity to ideal situation (FTOPSIS).
5. Discussion of the results and provision of partial validations of the risk assessment and decision-making models through the use of case studies with sensitivity analysis, in order to demonstrated a reasonable level of confidence in the results. This will be achieved in Chapters 4, 5 and 6.

The objectives are set out in order to achieve the aim of the research. The hypothesis is that it is possible to develop a maintenance and inspection strategy capable of tackling a variety of circumstances found in industry, with special consideration placed on machinery operating under a highly uncertain environment. This hypothesis must utilise historical data, available data and expert judgement using risk-based tools and techniques.

The test of the hypothesis relies on the application of the widely used uncertainty treatment methods such as the evidential reasoning, fuzzy logic, fuzzy rule base and TOPSIS. These methods can serve as the basic building blocks, as well as making a significant contribution to the development of a novel and advanced expert system, and decision-making models for condition monitoring of marine and offshore machinery.

## 1.4 Research Data Mining

Primary data:

- Test results from the industry laboratories
- Historic data from reputable oil companies
- Surveys from industry experts

Secondary data:

- Information from documents
- Published journals/reports
- Conference papers

## 1.5 Marine and Offshore Machinery Investments

A large-scale infrastructure project such as a ship in maritime transport or a floating production, storage and offloading in offshore investments affects the economic prosperity of nations across the globe. The design and construction of machinery systems for marine and offshore infrastructures inevitably involves a high degree of uncertainty. Figure 1.1 shows a $12bn Shell Prelude floating liquefied natural gas plant, and a Statoil's Oseberg offshore oil and gas field platform in the North Sea - typical marine and offshore investments with hundreds of machinery that need to be monitored and maintain for operational safety and reliability.


Figure 1.1: Typical Marine & Offshore Investments

**Sources**:https://www.theaustralian.com.au/news/bn-prelude-floating-plant-has-shell-fired-for-lng/news-story/ac91ce9c044be11681a5c6da79ddd057?sv=742721929c7b12b4cb3cbf2042fd9dbe

http://www.esa.int/spaceinimages/Images/2013/11/Offshore_platform

## 1.6 Researcher’s Background

The researcher have sound knowledge in modelling and simulation of marine and offshore machinery, maintenance and reliability of engineering systems, and with considerable working experience in both marine and oil & gas industries. He holds National and Higher diplomas in marine engineering, first and master’s degrees in “mechanical & marine” and “marine and offshore” engineering respectively. Currently working with Shell as services development & deployment engineer where he gains extensive insight into design, built, development and deployment of Shell LubeAnalyst planned maintenance platform based on oil condition monitoring plus the integration of other Shell customer value proposition, which are related to his research area. The researcher's education, and work experience provide a strong evidence of his knowledge in the research area.

# Chapter 2

## Literature Review

**Summary**

This chapter reviews the relevant literature that has influenced this research. The literature review reveals the contribution that this research makes to the marine and offshore industries. By doing this, it provides insights into the structure of the research, articulates ideas from other authors in a flexible manner as well as ensures that the research is independent and original in structure and composition. The work focuses on published studies regarding planned maintenance, condition (predictive) based maintenance, reliability centred maintenance, oil condition monitoring, and oil analysis. It then generates a further understanding within the subject area of study. This serves to position the research into the context of what is already known and what knowledge gaps exist. Finally, a framework emerges for further research of originality that avoids unnecessary repetition of existing research (Blaxter *et al*., 1996).

Relevant journals, magazines, textbooks, and conference papers are extensively reviewed. A number of studies from other relevant conference and journal articles, books and websites are sourced to provide a solid background for the proposed research. Collaborations are also made with experts using existing planned maintenance systems, researchers, lubricant laboratories and industries in the proposed subject to ensure that relevant data/information is tracked and monitored for the purpose of this research.

### 2.1 Introduction

Accidents have underpinned the need for practical and efficient condition monitoring of the machinery aboard ships. Engine failure, for example, in Savannah Express led to her subsequent contact with a link-span at Southampton docks in July 2005, and machinery breakdown and subsequent fire on-board Maersk Doha in October 2006 (MAIB, 2010). Due to economic needs, high safety, reliability, the need for their efficient operations in the face of disruption and adverse sea conditions, there is a strong desire for these machinery to be closely monitored, maintained and operated in such a manner that they can recover from design and human errors with little losses and less susceptible to breakdown.

This and many other reasons highlighted in the literature indicate a key factor that will ensure and assure the safety and continuity of operations of these machinery in the face of severe and catastrophic failure. When critical machinery such as cranes, main engines, etc., do not have the robustness to recover in the face of failure, the entire ship operations can be disrupted and delayed. Given that approximately 90% of the world's trade is transported by sea (IMO, 2006), the global economy is heavily dependent on the effective operation of marine and offshore machinery. Due to an increasing high level of systemic complexity, disruptions within their operation can be catastrophic and have long-term negative consequences.

Building an efficient planned maintenance system for machinery is thus crucial. To fulfil this requirement there must be a sustained engagement from the stakeholders involved in marine and offshore operations. Academics and industrialists have long acknowledged that purposeful maintenance can reduce catastrophic marine failures as it reaches a point of diminishing returns. Optimising the machinery's performance capability would require the establishment/adoption of a culture of a systematic maintenance in order to bring and maintain its operations to a desired level of functionality. By developing an effective maintenance framework for marine and offshore machinery operating under a highly uncertain environment, it provides a flexible and collaborative modelling of efficient planned maintenance system to address the risks of failure proactively, particularly as new machinery designs are constantly emerging.

## 2.2 An Overview of Marine and Offshore Industry

The marine and offshore industry operates in harsh environments, including a varying range of air and water temperatures, high-pressure conditions, salt water, and sea roughness. The complexity of marine and offshore machinery can be constructed (theorised) by components, and interacting functional connections with diverse and specific tasks in different conditions of operations. This constantly increasing complexity claims a constant improvement in ship powering, automation, specialisation in cargo transport, and new ship types. A well-planned effort is paramount to make the sea transport safer and more yielding. Therefore, the criteria of reliability, availability and maintainability have become very important factors in the process of marine and offshore machinery design, operation and maintenance.

Today's competitive market drives marine and offshore companies to improve quality, product variety, availability, and productivity whilst constantly reducing operations costs. Moreover, competition, which is intensified by technological innovations and a continuously changing market, creates opportunities for marine and offshore operators to examine every function of their business that is connerstoned by the maintenance of their machinery to achieve a competitive advantage (Pintelon *et al.*, 2006). The integration of the maintenance function with other operation functions would mean that a management system is needed to deal with reliability, availability and maintainability issues (Moubray, 2003).

### 2.3 An Overview of Maintenance Concepts and Practices

Maintenance is defined as ensuring that a facility, equipment or other physical asset continues to perform its intended functions (ABS, 2016). The ultimate goal of maintenance is to ensure the reliability of equipment, machines or processes so that they meet the business needs of the company. When maintenance is correctly developed and managed, it serves to preserve a company's assets to meet the need for reliability at an optimal cost. The importance of maintenance lies in its indispensable function in marine and offshore operations. The total cost of maintenance is extremely difficult to calculate because of the number of factors affected by the breakdown of a machine. Ashayeri *et al.* (1996) ascertain that these factors include:

- Disruption to operation.
- Downtime of failed equipment.
- Downtime due to inspection.
- Inefficient use of personnel.
- Repair time.
- Costs associated with all of the above.

Given these factors, the importance of maintenance should not be underestimated, as it is one of the areas that contribute heavily to marine and offshore machinery operations. Not only can effective maintenance extend the life of the machinery, but it can also improve marine and offshore operations as a whole. Anderson and Neri (1990) believe that successful maintenance policies help in reducing machinery downtime, improving quality and increasing productivity. Maintenance may be broken down into two main categories: reactive and proactive (Fredriksson and Larsson, 2012), which all the four widely known maintenance strategies (run-to-failure maintenance, preventive maintenance, condition-based maintenance, and reliability centred maintenance) fall into. Reactive maintenance responds to an identified need, for example, a breakdown of a machine or equipment. This maintenance approach (which is also referred to as the run-to-failure maintenance strategy) relies on the speed of the maintenance department to respond and react to be effective. The overall goal of reactive maintenance is to reduce response times and reduce equipment downtime. Proactive maintenance (which covers the preventive maintenance and condition-based maintenance strategies) according to Fredriksson and Larsson (2012) is primarily concerned with stabilising machines or equipment, and relies on the detailed assessment of equipment.

### 2.3.1 Run-To-Failure Maintenance (RTFM) Strategy

Run-to-failure maintenance is basically the "run it till it breaks" maintenance approach. It is also known as reactive maintenance (Sullivan *et al.,* 2010) or corrective maintenance (Toms and Toms, 2008). In this type of maintenance approach, no actions or efforts are taken to maintain the equipment, as the designer originally anticipated the use of the equipment until the design life is reached. However, Toms and Toms (2008) believe that this type of maintenance is the action of affecting repairs when some part breaks down or ceases to function properly.

<u>Advantages</u>

- Low equipment capital cost.
- Low operational safety issues.
- Fewer staff required.
- High equipment life cycle reliability.

<u>Disadvantages</u>

- Increases costs due to unplanned downtime of equipment.
- Increases labour costs, especially if overtime is needed.
- Costs involved with repair or replacement of equipment.
- Possible secondary equipment or process damage from equipment failure.
- Inefficient use of staff resources.

### 2.3.2 Preventive Maintenance (PM) Strategy

Preventive maintenance can be defined as an action performed on a time or machine-run-based schedule that detects, prevents, or mitigates degradation of a component or system, with the aim of sustaining or extending its useful life through controlling degradation to an acceptable level (Sullivan *et al.,* 2010). It is a periodic component replacement. According to Pillay and Wang (2003b), preventive maintenance (PM) is a maintenance strategy that is performed before equipment failure takes place. This method is often used in industry with routine inspections at set intervals.

Preventive maintenance is not the optimum maintenance program, but it does have several advantages over that of a purely reactive program. By performing the preventive maintenance as the equipment designer projected, the life of the equipment can be extended nearer to design. Preventive maintenance that involves lubrication, a filter change, etc. will generally ensure the efficient running of the equipment and will result in cost savings. While catastrophic equipment failures cannot be prevented, the number of failures can be decreased. Thus, minimizing failures can translate into maintenance and capital cost savings.

Advantages

- Increases equipment availability.
- Increases operational safety.
- Reduces unscheduled downtime.
- Improves workload distribution for easy management of maintenance.

Disadvantages

- Labour intensive and requirement of sufficient resources.
- Includes performance of unneeded maintenance.
- Unscheduled downtime not completely eliminated.
- High cost of equipment maintenance.

### 2.3.3 Condition-Based Maintenance (CBM) Strategy

Condition-based maintenance is a type of maintenance used in determining the optimum time at which to perform specific maintenance by monitoring the operation and condition of each component in a given application (Toms and Toms, 2008). According to Sullivan *et al.* (2010), CBM is also known as “Predictive Maintenance”, and can be described as an attempt to refine maintenance activities to only those times when they are functionally necessary, based on data collection, analysis, and (negative) trend determination from an established “healthy” base level. Condition-based maintenance is best used in situations where equipment is critical to operations and the appropriate monitoring system is reliable and economical. Condition-based maintenance uses non-intrusive testing techniques such as sensors, visual inspections or performance data in order to assess the condition of the equipment. Continual feedback of the condition of the equipment allows for the planning and scheduling or repairs before failure occurs (Sullivan *et al.,* 2010). The data collected in condition-based maintenance can be used in one of several ways in order to identify the causes of failure or simply the condition of the equipment:

- Pattern recognition - this is about understanding the relationship between certain events and failure.

- Tests against limits and ranges - alarms could be set at upper or lower limits to inform when a certain aspect of equipment moves outside the limits (Sherwin and Al-Najjar, 1999).
- Statistical process analysis - if there is published failure data on a component or system, a comparison of the failure data that has been collected on site with the published data can be useful to verify or disprove that the published data can be used for the analysis of a component or system (Arthur, 2005).

Advantages

- Increases equipment operational life/availability.
- Decreases in equipment or process downtime.
- Better product quality.
- Improves worker and environmental safety.
- Improves worker morale.
- Reduces maintenance running hours.
- Shortens repair times.
- Reduces spare parts requirements; therefore, decrease in costs for parts and labour.

Disadvantages

- Increases investment in diagnostic equipment.
- Increases investment in staff training.
- Savings potential not readily seen by management.

### 2.3.4 Reliability-Centred Maintenance (RCM) Strategy

Reliability centred maintenance (RCM) is a systematic approach to evaluate a facility's equipment and resources to a high degree of facility reliability and cost-effectiveness (Sullivan *et al.,* 2010). The philosophy of RCM employs the three maintenance strategies mentioned above in an integrated manner to increase the probability that a piece of equipment / component will function as expected over its design life cycle with minimum maintenance. The goal of this philosophy is to provide the stated function of the facility, with the required reliability, and at the lowest cost. One of the prerequisites of RCM is that maintenance decisions be based on maintenance requirements supported by rigorous technical and economic justification.

Advantages

- Can be the most efficient maintenance program.
- Lowers costs by eliminating unnecessary maintenance or overhauls.
- Minimises frequency of overhauls.
- Reduces probability of sudden equipment failures.
- Able to focus maintenance activities on critical components.
- Increases component reliability.
- Improves feedback to other organisations.

Disadvantages

- Can have significant start-up cost, training, equipment, etc.
- Savings potential not readily seen by management.

## 2.4 Current Status of Maintenance Management in the Marine and Offshore Industry

The marine and offshore industry by its unique nature and historical regulatory perspective has developed into an industry that is controlled by compliance. The vast majority of ships are built and operated to a minimum standard. However, according to Shorten (2012), less than 17% of world-class ships operate with an approved planned maintenance system, and the reason for this is not yet clear but may be entrenched by a power shift where control has moved away from the ship towards the office. Maintenance engineering and maintenance management are becoming more and more vital to the success of any ship operator. This is due to the high capital costs of machines and equipment as well as their high maintenance costs. Maintenance however can often be applied in a haphazard way, with poor integration of various maintenance techniques.

Often a company will implement one or more of the best known maintenance techniques such as RCM and CBM without inter-links to maintenance philosophy and even to their own business. In many companies, PM tasks can be perceived as unnecessary because they seem to be having little impact on machinery operations. Conversely, PM can also be over utilised, in the sense that PM activities are performed more frequently than is actually needed. While each of these will certainly contribute to the success of the maintenance department, the way in which they are introduced can often lead to future problems (Coetzee, 1999). As a result, maintenance planning in the marine and offshore industry today faces many challenges.

With the advancement of data collection techniques available to most marine and offshore companies, improvements in accuracy of failure data, diagnosis and prediction can be realised. The data collection process is attained using a maintenance management information system. The MMIS collects, processes, and transmits maintenance information, to be used by the maintenance personnel, managers, and those who need to make decisions, which may affect machinery operation and performance. Many organisations, however, have implemented the MMIS with different levels of success (Labib, 1998). Successful implementation of such a system depends on both the planning strategy of the company and the maintenance practice adopted.

Maintenance departments in the marine and offshore industry often utilise a general PM strategy with the integration of other maintenance philosophies. This maintenance approach is then fine-tuned to suit each individual company. This method has the potential to create problems such as establishing a root cause when a problem arises due to the multiple encrusted maintenance strategy. Implementation of new machines or equipment may also create problems, as the existing maintenance strategy has to cope with this change. Thus, Shorten (2012) recommends the use of a more specific and targeted method, which is to perform a formal consultative review of the current situation based upon a wider and less process-based analysis using industry experts who have first-hand experience of the difficulties faced in the application of efficient maintenance management practices.

## 2.5 Dealing with Uncertainty in Marine and Offshore Machinery Design and Operation

The main issue discussed in literature when designing machinery for operation in marine and offshore environment is about how to deal with uncertainties and unpredictable events that lead to the machinery's failure. This is because when such machinery does not have the robustness to recover in the face of failures, it poses a high level of risk to the entire marine operation. A more realistic way to optimise the machinery's capability is to incorporate planned maintenance culture into its operations to adapt to, cope with and recover to a desired level of functionality. Nevertheless, an emphasis on machinery maintenance provides a flexible and collaborative modelling of planned maintenance framework to address many risks of machinery failures proactively, particularly as new hazards and threats are constantly evolving.

Uncertainties are things that are not known or imprecisely known. Based on expert opinions, the lack of consideration of uncertainty in the design of marine machinery systems has led to unclear goals in their development with often no clarity in the short and long-term vision of the machinery operation, resulting in conflicting performance criteria. According to Daalhuizen *et al.* (2009), uncertainty is a fundamental element in machinery design because designers are often unable to predict the design process, and as a result, they may have to rely on the knowledge of the previous processes that led to the successful designs. Thus, uncertainties which are associated with complexity, multi-disciplinary issues, and outcomes that are unforeseeable in the early phase of the marine and offshore machinery operations are to be dealt with while working on the machinery design.

These and many more reasons necessitate a holistic approach towards marine and offshore machinery design and operation in order to optimise its efficiency. In response to the aforementioned challenges and in order to reduce or eliminate the effect of disruptions on marine and offshore operations, decision-makers are left with the task of implementing risk management programmes to address various concerns impacting on their operations. Several methods such as quantitative risk assessment, which has been used in the process/oil and gas industry (Delvosalle *et al.*, 2006), and formal safety assessment (FSA), used in the maritime industry to describe a rational and systematic risk-based approach for safety assessment (Wang and Trbojevic, 2007), (Pillay and Wang, 2003b), have evolved to address the particular need of stakeholders in a variety of ways.

Although FSA for maritime application is criticized by many researchers, Kontovas and Psaraftis (2009) affirm that the approach presents a great opportunity for relating safety and reliability engineering to maritime risk assessment for a better understanding of the machinery vulnerabilities in a very simplified manner. Risk analysis and strategic maintenance planning of marine and offshore machinery are treated as independent activities and implemented in different time frames. Little scope is left to incorporate flexibility into the front-end operations of the systems to anticipate, cope with and adapt to the ever-changing and dynamic environment. Patelli *et al.* (2015) claim that the aspect of managing the uncertainty in multi-disciplinary design of critical systems requires not only the availability of a single approach or methodology to deal with uncertainty, but it also requires a set of different strategies and scalable computational tools. The lack of a coherent and integrated approach has led to many parallel initiatives being devised by designers, resulting in overlap or neglect of the core responsibilities with long-term financial consequences. For critical components in important machinery used in marine and offshore operations, a factor of safety may not be sufficient to account for uncertainties, thus, it is imperative to consider reliability.

Risk composes of two elements, *frequency* and *consequence*. Risk is defined as the product of the frequency with which an event is anticipated to occur and the severity of the consequence of the event's outcome (ABS, 2016). Risks according to Knight (2014) are "*known unknowns"* while uncertainties are "*unknown unknowns"*. Knight (2014) further argues that risk will not generate profit, but can be calculated using theoretical models, or by calculating the observed frequency of events to deduce probabilities. Consequently, Zio and Pedroni (2012) claim that managing and treating uncertainty in risk assessment, maintenance management of complex systems is a major concern to analysts because the causes of uncertainty are diverse, and it occurs infrequently.

For example, based on the machinery design knowledge and operational experiences and data familiarization, analysts can predict the risk of failures of the machinery components before they occur (i.e. known unknowns), but based on the underlines uncertainty, analysts are unable to predict the severity of this failure and the cost to the operations (i.e. unknown unknowns). Besides, Knight (1921) further established that objective probability is the basis for risk, while subjective probability underlies uncertainty. Therefore, the deficiency of machinery risk assessment resulting from a lack of data or a high level of uncertainty should be compensated by the general valuation capacity of humans who are able to comprehend the essence of the subject matter in an unclear and imprecise situation.

## 2.6 Machinery Oil/Grease Analysis

In the early 1940s, Denver and Rio Grande Western Railway (DRGW) were the first to develop work in machinery oil analysis. But after the move from steam to diesel locomotives in the railway industry (Capasso *et al.*, 2015), oil analysis became firmly established as a reliable machinery monitoring technique. This programme was then used to determine the running condition of locomotive diesel engines. Today, most naval shipboard and aviation equipment is monitored by oil analysis as a pre-emptive measure against unscheduled equipment malfunction (Toms and Toms, 2008).

In today's exploding computer and information age, oil analysis has evolved into a mandatory tool in the predictive maintenance arsenal. Therefore, the goal of an effective oil analysis programme is to increase the reliability and availability of the machinery while minimising maintenance costs associated with oil change, labour, repairs, and downtime. Toms (1998) claims that accomplishing this goal takes time, training, and patience, while Barrett (2004) ascertains that the results are dramatic and the documentation savings in cost avoidance are significant.

Lube oil analysis is used extensively to help companies maintain their equipment, especially on-board ships following cases of accidents originated from machinery failures. While it is true that some failure mechanisms, such as misalignment, are better detected using vibration monitoring devices, most experts, including those that specialize in vibration analysis, recognize that oil analysis will generally detect active machine wear before vibration occurs for it to be detected by vibration monitoring device. Barnes (2008) is of opinion that the combination of oil analysis for early detection coupled with the advanced diagnostic capabilities of vibration analysis make the benefits of these two techniques far greater when treated as teammates rather than opponents.

The analysis of used lubricating grease has become a benchmark procedure as part of the UK Health and Safety Executive (HSE) guidelines on managing the safety of pedestal cranes, specifically in the offshore exploration and production industries. Considering the failure modes and the probability of such failures against the cost of performing the monitoring, the study found grease analysis to offer the most effective solution (Shorten, 2001).

The issue with grease analysis, however, is the veracity of the sample. The sample must be as representative as possible. A feature of grease analysis, as opposed to oil analysis, is that contaminants and wear debris are not uniformly distributed throughout the lubricant. This can lead to samples with huge variances in debris content.

## 2.7 Oil Sampling

The first step in any oil analysis program is obtaining oil sample. An oil sample is a major help in monitoring the quality of oil in a piece of machinery. The objective of sampling is to obtain a test specimen that is representative of the entire quantity. Thus, lab samples must be taken in accordance with the instructions in ASTM Practice D 4057. The specific sampling technique can affect the accuracy of this test method. Most lubricant condition monitoring services use an oil sample of only 100ml to represent a system that may hold hundreds or thousands of litres of oil. Regular sampling provides the information needed to continually maximize asset reliability and increase profits. However, this will only be achieved if every sample contributes to building an accurate history from which trends in wear, contamination, and degradation can be determined.

### 2.7.1 Oil Sampling Kit

Great care must be taken when using sampling kits to drawn off oil samples during transport at sea to ensure that the test results from the lab represent the state of the machinery. Figure 2.1 shows a typical oil sample kit that includes the following:

- Reinforced tubing with quick coupling connectors.
- Tubing with Luer Lock connection for syringes.
- Adaptors (screws: G1/2“; G3/8“; G3/4“; G5/8“).
- Screwing bottle cap with quick coupling connection.
- Multi-functional gripper.

- Sample packing envelop
- Sample submission label
- Tubing for oil discharge with quick coupling connection.


Figure 2.1: Oil Sampling Kit Box

### 2.7.2 General instructions for Correct Oil Sampling

- Ensure health and safety conditions by always taking particular care with high-pressure piping and thermal systems and any sampling close to electrical equipment.
- Ensure the quality of the sample is maintained by always taking the sample at the same point, in the same way and after the same amount of time. For example, if previously took the sample half an hour after the machine has been started, make sure that the next sample is taken half an hour after the start of the machine as well.
- Sample a component while it is running (if it is safe to do so) or within 30 minutes after shutdown. Always keep in mind to refrain from sampling right after a large volume of oil has been added.
- Always be sure to draw sufficient of the sample to fill the bottle. 80% full is a good level to aim for, as this will ensure that there is adequate sample to complete all tests and will ensure adequate ullage to allow sample agitation by the laboratory.
- Avoid contamination of the sample by always taking the sample in the most hygienic conditions. In this way, contaminating the sample, which could lead to an incorrect analysis, can be avoided.
- Always use the right sampling equipment and the bottles and make sure that they are clean. Clean the sampling kit immediately after use. After taking the samples, check to make sure that the bottles are tightly closed.
- It is important that the gun/bottle assembly is kept upright while in use to prevent oil entering the gun. Should this occur, disassemble it immediately and flush thoroughly with white spirit or kerosene. Dry before reassembling. **Note:** Never flush the gun with petrol or decreasing fluid.

### 2.7.3 How to Take a Good Oil Sample

1. Use a sample bottle; remove the cap and screw into the pump body.
2. Using a new length of tube for each sample, push the tube through the top of the pump until it appears half way down the sample bottle. Make sure to tighten the thumbscrew to secure the tube.
3. Place the end of the tube into the sampling point.
4. Ensure that the sample bottle is vertical throughout the sampling operation and that it is not overfilled.
5. Unscrew the bottle and immediately screw on the cap to avoid any contamination.
6. Complete the sample label, send the sample, and sample label to the laboratory.

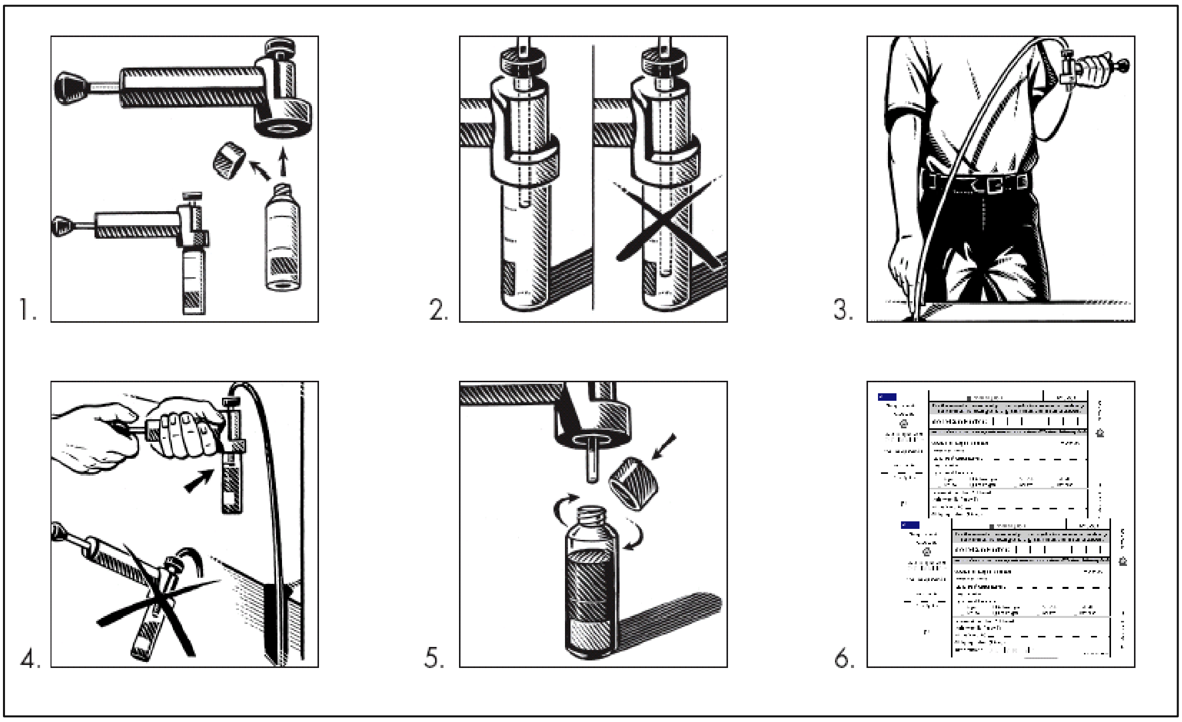


Figure 2.2: Steps to Take Good Oil Sample

### 2.7.4 Laboratory Oil/Grease Test Methods and Results

Most oil analysis requires test methods and these test methods are not straightforward; thus, necessitate having regulations to be carefully follow (Fitch, 2016). The regulations from standards provided by ASTM, ISO or other comparable standardization organizations are commonly used by the laboratories. These test standards define the generally accepted procedure, the proper application of the test, the method’s repeatability or reproducibility, calibration requirements and other relevant data (ASTM D445, ASTM D5185, ISO/IEC 17025, ISO 11500). For example, Iron (Fe) element in oil sample with a test result range 2

– 140 has a repeatability of 0.13 $X^{0.80}$ and reproducibility of 0.52 $X^{0.80}$, where $X$ = mean concentration, µg/g (ASTM D 5185, 2009).

Tests performed during an oil analysis to find the particles floating in oil sample include an ICP Spectroscopy, Particle Count, Ferrous Density, FT-IR**,** and Analytical Ferrography. Elements found in oil sample are measured in parts per million (PPM) - a very small amount. A single PPM is equivalent to 0.0001%. To put that in perspective, it takes 10,000 PPM to equate to 1.0%. Concentrations seen in oil analysis reports will be from one to several hundred PPM. The following elements are commonly the cause of component wear: iron, chromium, aluminum, copper, lead, tin, nickel, antimony, silver, titanium, and manganese.

### 2.8 Machinery Oil Condition Monitoring

According to Toms and Toms (2008), oil condition monitoring is the assessment of oil failure modes through the monitoring of reliable condition indicators. Machinery condition monitoring based oil analysis is beginning to gain its momentum in the marine industry as it is now regarded as a vital maintenance practice. It is worth mentioning that an effective oil analysis programme will keep not only engines, but other important assets such as gearboxes, hydraulic systems, turbines, compressors, generators and every other oil-wetted machinery, in operation by reducing unexpected failures and costly unscheduled down time.

The machinery condition monitoring based on oil analysis has been in use in general industry for almost two decades, and has proved its effectiveness and sensitivity to faults, giving plenty of warning to allow for maintenance activities to be planned and carried out with minimum disruption to operations and limiting the opportunity for costly secondary damage to occur (Bannister, 2007). The machinery condition monitoring based on oil analysis is also well suited for routine marine use where it can put the power of condition-based maintenance into the hands of every ship owner and offshore operator.

Many experts, such as Courrech *et al.* (2014), Galloway (2014), and many others, have conducted research in this area. Given that the input data for determining the condition of the machinery are normally expressed in both quantitative and qualitative terms, decision makers may often carry out their judgements based on both quantitative data and experiential subjective assessments of the machinery. Consequently, a proposed methodology for monitoring the condition of the marine and offshore machinery should be capable of processing both quantitative and qualitative data. Figure 2.3 shows the generic machinery oil condition monitoring cycle.

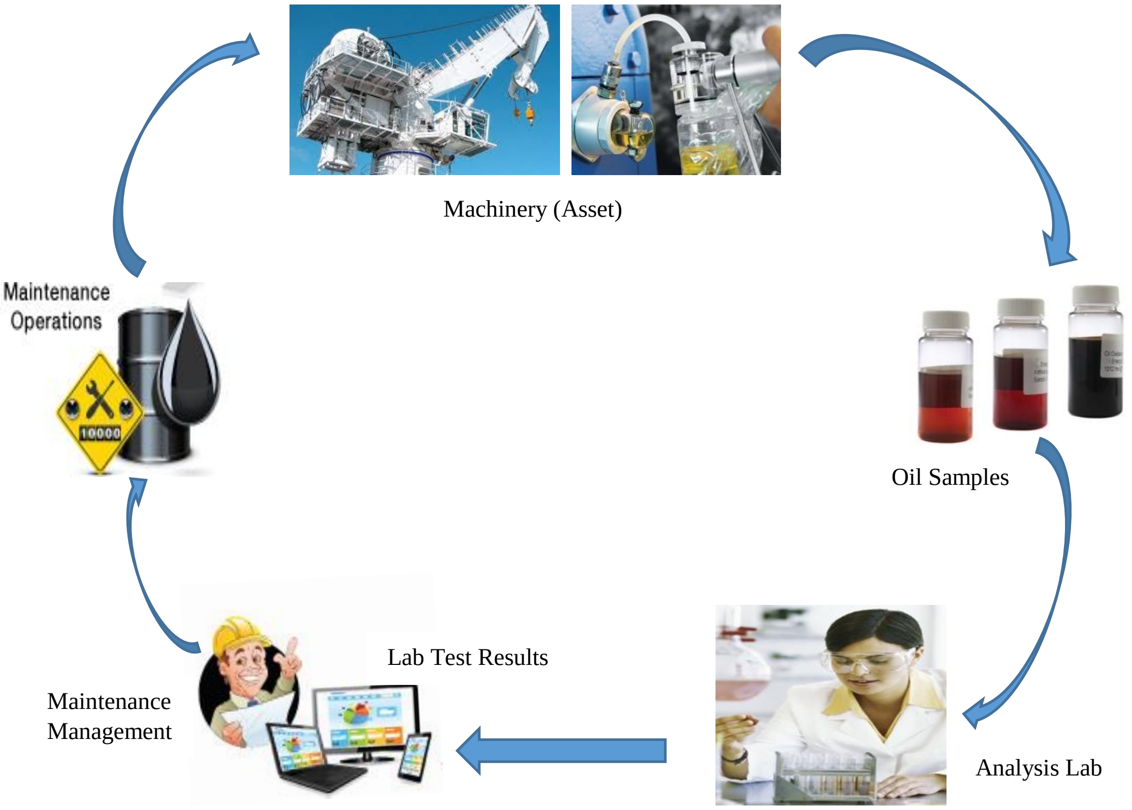


Figure: 2.3: Machinery Oil Condition Monitoring Cycle

## 2.9 Faces of Errors in Machinery Operation

The analysis of error in complex sociotechnical systems' operations is essential to the investigation of machinery failures. Errors are situations or events of high uncertainty that can lead to obstruction or impediment of a system's normal operations by creating discontinuity, confusion, disorder or displacement of its functions in a dynamic environment (Madni, 2007). It is the state or condition of being wrong in conduct or judgement. These adverse situations can take a variety of forms such as operational contingencies, defects in design, and human mistakes. According to Whittingham (2004), two types of errors can occur in machinery:

1) Internal error.
2) External error.

These types of errors must be evaluated in order to ensure that machinery cope with the adverse effect of disruption that may arise due to these errors. Thus, since disruptions are uncertain due to the nature of their occurrence, scenarios that lead to their occurrence may be defined probabilistically.

### 2.9.1 Internal (System Design) Error

The advancement in technology has cause the demand of high accurate parts to become a conventional need in the marine and offshore industry. With this progress in technology, errors in machinery design still become the norm in many of the marine and offshore machinery. The errors in machinery design are often associated with knowledge-based tasks and it is open to speculation as to exactly what the designer was thinking at the time the error was made (Whittingham, 2004).

### 2.9.2 External (Human) Error

External error in machinery operation in this context involves mainly human errors. Human errors can occur in different forms and can be exhibited in immeasurable manners.
In complex systems, such as vessels and commercial ships, the ability to understand and influence human behaviour is essential to ensure safety and reliability (Barbarini and de Andrade, 2010). Thus, as machinery systems are now becoming more complex, the difficulties of the human operator in managing the new technologies are exacerbated and the possibilities for machinery failure due to human error are increasing. Due to the growing imbalance between system reliability and human reliability, the need arose for methods of assessing the frequency or probability of a human error in the operation of technical systems. This need was supported by the developing science of ergonomics, which attempted to overcome the problem of human error by addressing how the design of the interface between human and machine could take more account of human capabilities and limitations (Whittingham, 2004). There are two basic approaches to the design of equipment from a human error point of view (Whittingham, 2004):

1) The system-centred approach. Emphasis is placed upon the system rather than the human being.
2) The user-centred approach. The system is matched as closely as possible to human capabilities and limitations.

Regrettably, up until now, many machinery designers have not fully understood the need to adopt a *user-centred approach* and there are numerous examples of complex technological systems on-board ships that have been designed mainly with system functionality in mind, but ignoring the capabilities and limitations of the user (Whittingham, 2004). Such systems invariably will result in degraded levels of human performance with severe consequences for reliability, equipment availability and safety. Systemic sources of error cover human-related elements, automated design systems and a combination of the two. It is worth mentioning that both human and design sources of errors can be referred to as agents of a system and can be seen as a source by which to respond to and recover from errors (IAEA, 2007 and 1991).

## 2.10 Lessons from Major Accidents in the Marine and Offshore Industry

This section describes a selected set of accidents within the marine and offshore industry where strengths and weaknesses are expressed in terms of either the robust attributes, personnel training and related concepts, or in terms of specific analytical processes that may have been neglected, such as design requirements, verification, reliability or interface management. Based on Jackson (2010), reviewing past accident events and scenarios has the following advantages:

- Provides insights into how a disruption can be survived even if it is not avoidable.
- Provides an avenue for system definition.
- Provides the basis for risk analysis of the system in order to reveal its vulnerabilities.

Many cases of disruption reported in databases were a result of near misses and other incidents, which are potential accident indicators. The research conducted by Leveson *et al*. (2005) and Reason (1997) acknowledged the importance of the proactive evaluation of near misses and incidents in order to assess the potential accident occurrence in a systematic fashion. The literature review revealed a strong correlation between the causes of near misses and major accidents, which have led to disruption of operations within the high reliability organisations (Wright and Van der Schaaf, 2004). Based on the report released by Marine Accident Investigation Branch (MAIB) in 2010, a total of 141 accidents were recorded for merchant vessels, of which a total of 25 accidents were caused by machinery failure, amounting to 18% of the total accidents recorded for the merchant vessels in 2010. However, this figure can be reduced when an effective and efficient planned maintenance tool is in place to address the most relevant deterioration and failure mechanisms.

### 2.10.1 Savannah Express Engine Failure

On July 19, 2005 at 1146 hours, the *Savannah Express*, one of the largest container ships in the world, a German flagged, weighing 94,483 gross tonnes was maneuvering prior to berthing at Southampton Container Terminal, when her main engine failed. The engine was unable to be started astern to reduce the vessel’s headway, and she made contact with a linkspan, which was seriously damaged.

The investigation report by MAIB (2006) reveals that the engine control system had suffered a series of technical problems since the vessel had come into service. The report also reveals that the *Savannah Express* was equipped with a slow speed diesel engine of a novel design, with no mechanical timing gear (including camshaft and timing chains or gears) but, instead, was fitted with a fully integrated, and computer controlled, electrohydraulic control system. The vessel's first chief engineer had attended a basic training course designed by the engine manufacturers. However, the engineer officers onboard at the time of the accident had not received any type specific training from the engine manufacturers. Thus, they were unable to correctly diagnose the reason for the engine fault at the Nab Tower and, later, at the Upper Swinging Ground.

The increasing levels of electrification of engine control and propulsion systems required more training in the operation, maintenance and fault finding of these technically complex, and multi-discipline systems. MAIB (2006) claims that the STCW training standards for ships' engineers have not been updated to account for modern system engineering requirements. The accident has also highlighted the essential need for the machinery manufacturers to develop an adequate type specific training course for the operators, and for International Maritime Organization (IMO) to improve training requirements for ships' engineers and electricians.

### 2.10.2 FPSO Cidade De São Mateus Explosion

On Wednesday February 11$^{th}$, 2015 at approximately 1130 hours, an explosion occurred on-board the floating production storage and offloading (FPSO) unit *Cidade de São Mateus*, once operated by BW Offshore Brazil Ltd, in the field under concession of Petróleo Brasileiro S. A (Petrobras). Based on the investigation report by ANP (2015), the explosion occurred due to the leakage of the condensed material into the pumps room, when the officers on-board attempt to drain the liquid waste from the central cargo tank, with the utilization of the alternative pump (stripping pump).

Nine people were reported dead in the explosion while twenty-six others were injured. There was also damage to the facility. The accident is recorded as the most serious oil and gas incident that has ever happened in Brazil in the last 14 years. The report reveals that this deadly incident was caused by series of technical failures, incomplete procedures, poor managerial decision-making, and improper training of the personnel on-board the vessel. It cited a failure to follow improper fluid pumping procedures as well as the installation of an incompatible piece of equipment as the main causes of the explosion.

The investigation report identified 28 root causes, all of which are correlated with the requirements established by ANP Resolutions No. 43/2007, and 61 recommendations, setting additional requirements in the report. Some of the recommendations in the report include:

- Inclusion of equipment information and critical systems arising from safety studies in computerized integrity management systems before the operation.
- Inclusion of critical procedures related to maintenance, inspection and testing in computerized integrity management systems.
- Updating the previously existing systems in converted ships to platforms at the time of conversion, considering the same design criteria and safety philosophy of the processing plant.

### 2.10.3 Maersk Doha Machinery Breakdown

On October 1st, 2006, the container vessel, *Maersk Doha* was in Norfolk, Virginia loading and unloading containers as she was scheduled to depart at 2100hrs but was delayed until midnight. The engineers took the opportunity to do maintenance work on the main engine and the auxiliary boiler was kept running with its feed water circulating through the exhaust gas economizer to keep it warm and ready for sailing. The problems began as one of the generators proved hard to start and a faulty reversing mechanism on the main engine left one cylinder stuck in the reverse position restricting her speed to 16 knots.

At about 0200hrs, a rapid rise in the temperature of the EGE was noticed and the Chief engineer realised that there was a fire inside the EGE casing. According to the MAIB (2007) report, the most likely cause of the fire was a malfunction of the auxiliary boiler control mechanism, which allowed the burner to keep firing with too little water in the boiler. This overheated the furnace, causing the distortion and cracking of the fire tube. As feed water was lost through the crack, the supply of water to the EGE failed, causing it to overheat. Soot deposits, which had accumulated within the EGE, then ignited. It is likely that the temperatures in the EGE rose sufficiently high for hydrogen and iron fires to develop. Inappropriate techniques were used to fight the fire initially, because either the crew lacked the understanding of the construction of the EGE or how to deal with the fire effectively.

However, the vessel had an extensive quality and safety management system (QSMS), but it lacked sufficient detail to assist the crew in dealing with either the machinery breakdown, or the subsequent fire. Further problems became evident during the emergency when other equipment did not work correctly. The records of emergency drills and maintenance of machinery made it difficult for the vessel’s managers to assess the quality of the work being carried out on-board. Neither these systems, nor the quality and technical audits carried out on the vessel, had been able to detect the underlying condition of equipment which subsequently failed during the emergency. Further measures were instigated to change emergency procedures and improve response of the entire ship.

## 2.11 Proposed Risk and Decision-Making Management Model

Against the background that traditional engineering risk and reliability analyses provide a general framework for the identification of uncertainties and quantification of risks, the application of this process to marine and offshore machinery safety management would facilitate the identification of stochastic variables and quantification of the associated risks in machinery operations. The techniques applied so far in assessments of the ship's crane have been based on assessment end-points that are either component-specific or based on matching similarities. It is however pertinent to note that the likelihood of component failure establishment and maintenance strategies in a particular machinery is inarguably a subject of probability, because the boundaries of machinery operations are notoriously vague, and risk estimation in the marine and offshore environment can be characterised by uncertainty and variability.

### 2.11.1 Risk Analysis Techniques

In this section, the generic risk analysis techniques proposed in this research work will be discussed. The model utilises fuzzy logic in combination with the fuzzy set technique to identify hazards associated with a crane of a floating production, storage and offloading (FPSO) vessel. Fuzzy logic theory has been applied in this model because the risk factors inherent in FPSO machinery are often incomplete and sometimes ill-defined for which traditional quantitative risk assessment approaches do not give adequate answers and solutions.

#### 2.11.1.1 Fuzzy logic theory

Fuzzy logic theory was developed in 1965 by Zadeh as an extension of classical Boolean logic from crisp sets to fuzzy sets and grew to become the first new method of dealing with uncertainty and problems that are too complex or ill-defined to be susceptible to analysis by convectional techniques. Aside from modelling the qualitative aspect of human knowledge and the reasoning process without employing precise quantitative analysis, fuzzy logic does not require an expert to provide a precise point at which a risk factor exists (Liu *et al*., 2004). Fuzzy logic has been applied in many fields and applications that include: engineering; research and development projects; business management; information and control; economics and marketing; education; health and medicine; safety engineering; risk modelling and management; and decision making analysis (Wang *et al*., 1995). Various fuzzy logic techniques have been used in uncertainty treatment. They include fuzzy sets and fuzzy rule-bases.

#### 2.11.1.2 Fuzzy set theory

The use of natural language to express perception or judgement is always subjective, uncertain, imprecise or vague (Wang and Chang, 2007). Such uncertainty and imprecision have long been handled with probability and statistics (Dubois and Prade, 1997). Notable among the methods of representing and reasoning with uncertain knowledge are Bayesian probability theory (Pearl, 1988); Demspster-Shafer theory of evidence (Shafer, 1978), (Dempster, 1969), (Dempster, 1968b), and fuzzy set theory (Liu *et al.*, 2003), (Zadeh, 1965). Fuzzy set theory (FST) was devised by Zadeh to provide an approximate and yet effective means of describing the behaviour of situations which are too ambiguous to allow mathematical analysis. It employs human analysis and linguistic variables to represent risks and model uncertainty inherent in natural language (Zadeh, 1965). It is therefore complementary to traditional safety analysis methodologies and can be an effective tool in dealing with ill-defined and imprecise information, especially linguistic information (Duckstein, 1994).

#### 2.11.1.3 Fuzzy membership functions

A membership function, normally referred to as 'MF', describes the degree of membership of a value in a fuzzy set. Membership function can be express as $\mu(x)$ where x is the value being fuzzified. There are many types of membership function, namely:

- Singleton
- Rectangular
- Triangular
- Gaussian

Depending on the problem being considered, any one of the above membership functions can be used to solve that particular problem.

Fuzzy membership functions and linguistic terms are extensions of numerical variables which can represent the condition of an attribute at a given interval by taking fuzzy sets as their values (Wang, 1997). They are generated by utilising the linguistic categories identified in the knowledge acquisition stage and consist of a set of overlapping curves used to define the fuzzy input subset from an input variable.

##### *2.11.1.3.1 Degree of membership*

Items can belong to a fuzzy set to different degrees: degrees of membership. An item that is completely within a set has a membership degree of 1, while those completely outside a set have a membership degree of 0. All degrees of membership must sum to 1. An item can be both A and not-A to different degrees e.g. A to a degree of 0.8, not-A 0.2. Degrees of membership are expressed with membership functions. The range of values a variable can take is called the universe of discourse (Watts, n.d).

#### *2.11.1.3.2 Triangular membership functions*

For the purpose of this work, only triangular membership functions will be considered in detail. Amongst the various shapes of fuzzy numbers, the membership function of the triangular fuzzy number (TFN) is the most popular and frequently used. A triangular fuzzy number is a fuzzy number represented with three points, as follows:

$A = (a, b, c)$

This representation is interpreted as membership functions (Figure 2.4).

$$\mu_A(x) = \begin{cases} (x-a)/(b-a), & a \le x \le b \\ (c-x)/(c-b), & b \le x \le c \end{cases}$$

where, $a$ and $b$ stand for the lower and upper bounds of the TFN respectively, and $c$ for the modal value.

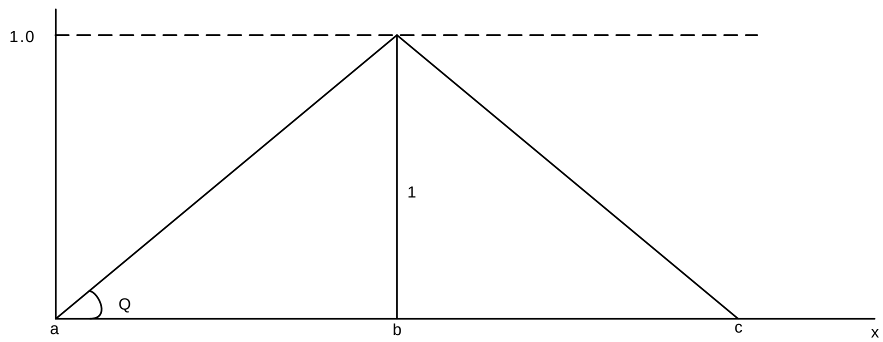


Figure 2.4: Membership Function of the Triangular Fuzzy Number

The TFN can be denoted by $\tilde{F}_n = (a_n, b_n, c_n)$ and the following operational laws of two TFN can be applied:

$\tilde{F}_1 = (a_1, b_1, c_1)$, and $\tilde{F}_2 = (a_2, b_2, c_2)$

Fuzzy number addition is calculated as:

$$\tilde{F}_1 \oplus \tilde{F}_2 = (a_1, b_1, c_1) \oplus (a_2, b_2, c_2) = (a_1 + a_2,\ b_1 + b_2, c_1 + c_2) \quad (2.1)$$

Fuzzy number multiplication is calculated as:

$$\tilde{F}_1 \otimes \tilde{F}_2 = (a_1, b_1, c_{1)} \otimes (a_2, b_2, c_2) = (a_1 a_2,\ b_1 b_2, c_1 c_2) \quad (2.2)$$

for $a_1, a_2 > 0;\ b_1, b_2 > 0;\ c_1 c_2 > 0$

Fuzzy number subtraction is calculated as:

$$\tilde{F}_1 \ominus \tilde{F}_2 = (a_1, b_1, c_1) \ominus (a_2, b_2, c_2) = (a_1 - c_2,\ b_1 - b_2, c_1 - a_2) \quad (2.3)$$

Fuzzy number division is calculated as:

$$\tilde{F}_1 \oslash \tilde{F}_2 = (a_1, b_1, c_1) \oslash (a_2, b_2, c_2) = (a_1/c_2,\ b_1/b_2, c_1/a_2), \quad (2.4)$$

For $a_1, a_2 > 0;\ b_1, b_2 > 0;\ c_1 c_2 > 0$

Fuzzy number reciprocal is calculated as:

$$\tilde{F}_1^{\ -1} = (a_1, a_1, c_1)^{-1} = (1/c_1, 1/b_1, 1/a_1) \quad (2.5)$$

For $a_1, a_2 > 0;\ b_1, b_2 > 0;\ c_1 c_2 > 0$

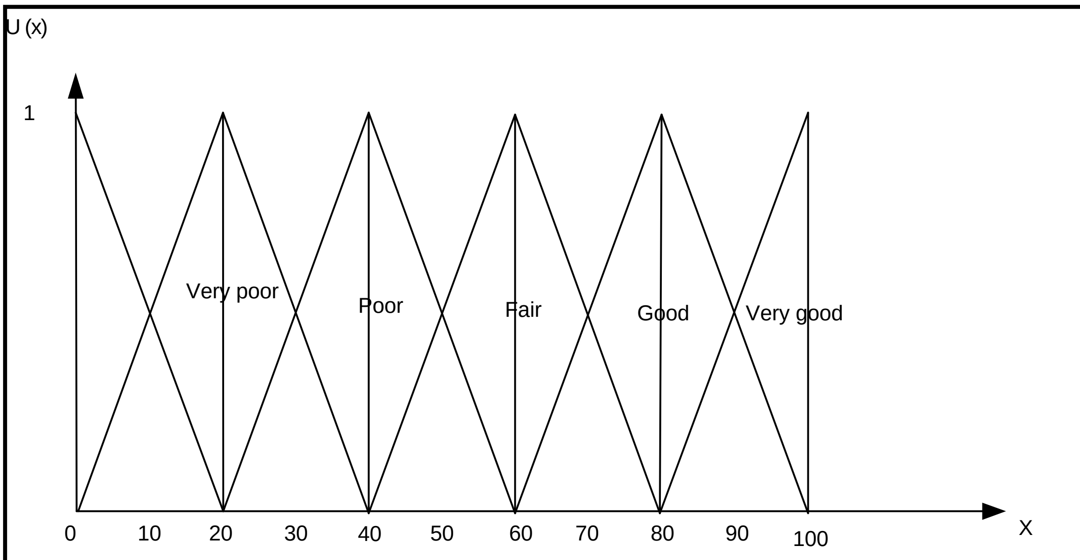


Figure 2.5: Membership Functions of Linguistics Variables for Measuring the Performance Value of Alternatives

### *2.11.1.3.3 Linguistic variables*

A linguistic variable is a variable whose values are words or sentences in a natural or artificial language. According to Zadeh (1975), it is very difficult for conventional quantification to express reasonably those situations that are clearly complex or hard to define. Therefore, the concept of a linguistic variable is necessary in such situations. Linguistic variables are currently being used extensively. The linguistic effect values of the best metal element alternatives found in this study are primarily used to assess the linguistic ratings given by the evaluators. Here each membership function (scale of fuzzy number) is defined by three parameters of the symmetric triangular fuzzy number: the left point, middle point, and right point of the range over which the function is defined.

Moreover, linguistic variables are used as a way to measure the performance value of the best metal element alternative for each criterion as "very good," "good," "fair," "poor" and "very poor" (Chen *et al.,* 2009). TFN, as shown in Figure 3.2, is used to indicate the membership functions of the linguistic terms. The horizontal axis indicates the quantitative number and the vertical axis indicates the degree of belief (membership value). If any quantitative number $(e.g.\ h_i)$ is found in the range of $h_{n+1,i}$ (with a grade $H_{n+1}$) and $h_{n,i}$ (with a grade $H_n$), its belief degrees can be evaluated as follows:

If $h_{n,i} < h_i < h_{n+1,i}\ then\ \beta_{n,i} = \frac{h_{n+1,i} - h_i}{h_{n+1,i} - h_{n,i}}$ (2.6)

$\beta_{n+1,i} = 1 - \beta_{n,i}$ (2.7)

where, $\beta_{n,i}$ is the degree of belief of the concerned quantitative number with the grade $H_n$, and $\beta_{n+1,i}$ is the degree of belief of the concerned quantitative number with the grade $H_{n+1}$.

2.11.1.4 Fuzzy rule-base method

A fuzzy rule-base allows more coherent and intuitive simulation for evaluating risk in marine and offshore operations. There has been a significant increase in the number and variety of applications using fuzzy rule based approaches. Zadeh (1965) first introduced the fuzzy set theory as a classical set for grouping together elements that all have at least one common characteristic (MIT GMBH, 2006), as cited by Ramezani and Memariani (2011). The fuzzy rule-based method does not require a utility function to define the probability of occurrence, severity and detectability considered for the analysis (Pilay and Wang, 2003a). A fuzzy rule base provides a coherent and intuitive model for evaluating faults in marine machinery.

One realistic way to analyse a risk with incomplete objective data is to employ a fuzzy *IF-THEN* rule built from human understanding, where premise and conclusions contain the linguistic variables used to describe risk parameters (Yang *et al.,* 2009). Such a rule has been used because probabilistic risk assessment (PRA) is considered inadequate to address the need of complex systems with high degrees of uncertainty. For example, *IF-THEN* rules with a belief structure can be constructed to simulate a maintenance management scenario. An *IF-THEN* rule can be developed as follows:

If Threat Likelihood is “Medium”, Machinery Vulnerability is “High” and Impact or Consequent Severity is “Serious”, then Machinery Failure is “High”.

Due to the high degree of uncertainty associated with the expert judgement when forming or representing a relationship between premise and conclusion, or rather, when the evidence available is not adequate to support any viable decision, or when the expert is not 100% sure whether to believe in an assumption, but only to a certain degree of credibility, it is possible to have fuzzy rules with a prudent belief structure as follows:

If Threat Likelihood is “Medium”, Machinery Vulnerability is “High” and Impact or Consequent Severity is “Serious”, then Machinery Failure is {(Very Low, 0), (Low, 0), (Medium, 0.6), (High, 0.4), (Very High, 0)}.

In light of the above, {(Very Low, 0), (Low, 0), (Medium, 0.6), (High, 0.4), (Very High, 0)} is a belief distribution of the machinery evaluation where experts are 60% sure that the machinery failure level is Medium, and 40% sure that the machinery failure level is High.

### 2.11.2 Decision Making Analysis Techniques

According to Reichert *et al.* (2007) as cited in John *et al.* (2014), decision analysis techniques were originally developed to support individual decision makers in carefully considering all aspects of the decision making process. Nonetheless, Ananda and Herath (2003) and Marttunen and Hamalainen (1995) are of the view that because these techniques are used to structure the problem under consideration and to make clear the expectations about outcomes and preferences, they can also be used to support group decisions as well as communicating decisions.

The significant issues described in literature for the effective application of multiple criteria decision making (MCDM) revolve around the information and data available to characterize a piece of equipment, and the related uncertainties that affect the models and parameters supporting the decision process. Several decision making problems involve uncertainty; thus, methods that facilitate better and optimum management decisions must account for variations in decision makers’ preferences for attributes and conflicting interests in a systematic fashion. As the complexity of decisions increases in complex machinery, it becomes more challenging for decision makers to identify appropriate alternatives. As a result, robust but flexible analytical tools that can account for these difficulties are required to consider the numerous criteria and decision outcomes (John *et al.,* 2014).

Risks, benefits and costs are considered the most important attributes associated in all decision making problems. This research is an attempt to use quantitative risk assessment (QRA) to support correct decision-making and improve the condition of marine and offshore machinery operating under highly uncertain environment. Quantitative risk assessment is a formal and systematic risk analysis approach used in quantifying the risks associated with the operation of an engineering process. Therefore, it is important to establish the link between QRA and some decision analysis techniques in a formal, systematic and transparent manner. A brief description of the MCDA techniques applied in these models is briefly discussed in the ensuing subsections.

#### *2.11.2.1 Fuzzy analytic hierarchy process*

Fuzzy analytical hierarchy processing (FAHP) method is an approach that employs the structuring of criteria of multiple options into a system and subsystem hierarchy of a complex engineering product like a ship. This includes relative values for all criteria and comparing alternatives for each particular criterion and further defining the average importance of alternatives using the concept of FST in a hierarchical analysis. When considering a group of attributes for evaluation, the main objective is to provide sufficient judgements on the relative importance of these attributes to ensure that those judgements are made appropriately (Pillay and Wang, 2003). FAHP modelling is employed in this work to calculate the weight of each criterion in a simplified and straightforward manner based on pair-wise comparisons. Given the differences in weights of the risk elements and their contributions to the failure of the marine and offshore machinery, FAHP can be utilised to solve the dynamic risk information loss in the hierarchical level of the model, while ensuring the progression of a smooth risk assessment from the bottom level of each subsystem's hierarchy to the goal's level (failure level).

One paramount advantage of FAHP is its ability to be integrated with other techniques such as the ER approach in risk assessment. FAHP offers a unique and effective way of modelling a system's uncertainties that is different from the conventional AHP. The initial work on FAHP was made by Laarhoven and Pedrycz (1983). They described fuzzy ratios by triangular fuzzy numbers (TFN) and computed weights using the logarithmic least square method. Buckley (1985), who proposed a geometric means to solving fuzzy weight priorities and performance scores, identified shortcomings in the initial work. Boender *et al.* (1989) modified the initial work on normalisation by integrating a regression equation. Cheng (1996) introduced a robust approach for handling FAHP using TFNs for pair-wise comparison and the extent analysis method for the synthetic extent values of the pair-wise comparisons. Zhu *et al.* (1999) made improvements on the extent analysis theory.

Deng (1999) presented an improved fuzzy-based approach for tackling multi-criteria analysis problems in a simplified manner and making them more interesting. Lee *et al.* (1999) further proposed a novel method based on the stochastic optimisation to achieve global consistency. Leung and Cao (2000) also discussed the consistency issue and proposed a concept of fuzzy consistency and tolerant deviation. Chou and Liang (2001) presented a fuzzy multi-criteria decision-making model by combining FAHP and the entropy concept for shipping company performance evaluation under uncertainty.

Furthermore, Yu (2002) proposed a robust computational programming goal method for fuzzy priority vectors, while Kuo *et al.* (2002) developed a decision support system for locating a convenience store. Arslan and Khisty (2005) proposed a set of “if-then” rules to select the cognitive comparison made between each alternative. Other details regarding the application of this method include: the evaluation of services; generation of weight from interval comparison matrices using the two-stage logarithmic goal programming method; an algorithm for evaluating naval tactical missile systems; evaluation of machine tool alternatives with quantitative variables; new product development processes; quality function deployment; project risk evaluations; computer integrated manufacturing systems selection; personnel selection problems; selecting wastewater facilities at prefecture level; evaluating wafer supplier in the semiconductor industry; and supplier selection in washing machine companies (Kilincci and Onal, 2011), (Cheng *et al.,* 2009), (Gungor *et al.,* 2009), (Anagnostopoulos *et al.,* 2007), (Ayag and Ozdemir, 2006), (Tuysuz and Kahraman, 2006), (Wang *et al.,* 2005), (Mikhailov and Tsvetinov, 2004), (Bozdag *et al.,* 2003) and (Kwong and Bai, 2003).

The conventional AHP method has been widely used and accepted to solve complex multi-criteria decision making problems, but its major shortcoming is that it uses a scale of one to nine (1-9), which, in many circumstances, cannot handle uncertainty in comparison of the attributes and also does not reflect the experts’ imprecise subjective judgements associated with uncertainty. FST is incorporated into the main steps of AHP to perform a rigorous analysis using fuzzy ratios instead of the conventional crisp values in AHP. This is to ensure that uncertainty is reflected in the process of the entire risk assessment from the bottom level to the goal level.

##### 2.11.2.1.1 Forms of analytic hierarchy process

Decision makers in a variety of industries use different forms of AHP. The two most commonly and widely used are:

i. The original version of AHP developed by Dr Thomas L. Saaty (Saaty, 1983). The original AHP version calculates the $n^{th}$ root of the product of the pair-wise comparison values in each row of the matrices and then normalizes the aforementioned n^th root of products to obtain the corresponding weights and ratings.

ii. The modified AHP version, which normalizes the pair-wise comparison values within each of the matrices and then averages the value in each row to obtain the corresponding weights and ratings.

#### *2.11.2.1.2 The geometric mean method (GMM)*

The geometric mean method is commonly employed in the AHP to combine the opinions of different experts when they have equal weightages in forming the group opinion (Ramanathan *et al.*, 1994). In this procedure, the geometric mean of the values provided by the experts is entered into the pairwise comparison matrix and then the eigenvector of the positive reciprocal matrix are computed.

For example, in computing element $i$ with element $j$, if $e_{ij}^1, e_{ij}^2 \dots \dots e_{ij}^N$ are the individual judgements made by experts 1, 2 ….., N respectively, then under the geometric mean method, the combined judgement value to be entered in the group pairwise comparison matrix, according to Saaty (1989) is:

$$(e_{ij}^1 \times e_{ij}^2 \times \dots \times e_{ij}^N)^{1/N} \qquad (2.8)$$

Aczel and Saaty (1983) proved that the geometric mean is consistent and satisfies the four axioms underlying the AHP theory. One important property of the geometric mean is its ability to dampen the effect of very high or low values, where such values might bias the arithmetic mean. In other words, the geometric mean is less affected by extreme values than the arithmetic mean.

### *2.11.2.2 Analytic hierarchy process algorithm*

A weight can be assigned to each criterion by using established methods such as simple rating methods or more elaborate methods based on pairwise comparisons. Using the AHP to calculate the relative importance of each attribute requires a careful review of its principles and background (Saaty, 1990). When considering a group of attributes for evaluation, the main objectives of this technique are to provide judgements on the relative importance of these attributes and to ensure that the judgements are quantified to an extent that permits quantitative interpretation of the judgement among these attributes (Pillay *et al.,* 2003a). The quantified judgements on pairs of attributes $A_i$ and $A_j$ are represented by an n-by-n matrix E. The entries $a_{ij}$ are defined by the following entry rules.

Rule 1: If $a_{ij}$ = α, then $a_{ji}$ = $1/\alpha$ , α ≠ 0

Rule 2: If $A_i$ is judged to be of equal relative importance as $A_j$, then $a_{ij}$ = $a_{ji}$ = 1.

According to above rules, the matrix E has the form as follows:

$$E = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix}$$

where, $i$, $j$=1, 2, 3..., n and each $a_{ij}$ is the relative importance of attribute $A_i$ to attribute $A_j$. Having recorded the quantified judgements of comparisons on pair ($A_{i,}$ $A_j$) as the numerical entry $a_{ij}$ in the matrix E, what is left is to assign to the n contingencies $A_1$, $A_2$, …, $A_n$ a set of numerical weights $w_1$, $w_2$, …, $w_n$ that should reflect the recorded judgements.

In general, the weights $w_1$, $w_{2\ldots,}$ $w_n$ can be calculated (Pillay *et al.*, 2003a) using the following equation:

$$w_k = \frac{1}{n}\sum_{j=1}^{n} \frac{a_{kj}}{\sum_{i=1}^{n} a_{ij}} \ (k = 1, 2, 3, \ldots, n) \tag{2.9}$$

where, $a_{ij}$ represents the entry of row $i$ and column $j$ in a comparison matrix of order $n$. The weight vector of the comparison matrix provides the priority ordering. However, it cannot ensure the consistency of the pairwise judgements. Hence the AHP provides a measure of the consistency for the pairwise comparisons by computing a consistency ratio (CR). The CR informs the decision makers how consistent they have been when making the pair-wise comparisons (Kunz, 2010). It is designed in such a way that a value greater than 0.10 indicates an inconsistency in the pair-wise judgements and according to Andersen *et al.* (2008), the decision maker should review the pair-wise judgements before proceeding.

Consequently, if the CR is 0.10 or less, the consistency of the pair-wise comparisons is considered reasonable, and the AHP can continue with the computations of the weight vectors. A higher number means the decision maker has been less consistent, whereas a lower number means the decision maker has been more consistent (Kunz, 2010). If the CR is > 0.10, the decision maker should seriously consider re-evaluating the pair-wise comparisons. The source(s) of inconsistency must be identified and resolved and the analysis re-done. The CR value is computed according to the equations (Andersen *et al.,* 2008).

$$CR = \frac{CI}{RI} \tag{2.10}$$

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2.11}$$

$$\lambda_{max} = \frac{\sum_{j=1}^{n}\left[\left(\sum_{k=1}^{n} w_k a_{jk}\right)/w_j\right]}{n} \tag{2.12}$$

where, CI is the consistency index, RI is the average random index, $n$ is the matrix order as shown in Table 2.1 (Saaty, 1990) and $\lambda_{max}$ is the maximum weight value of the $n\text{-}by\text{-}n$ comparison matrix E.

**Table 2.1:** Value of RI versus Matrix Order

| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| RI | 0 | 0 | 0.58 | 0.9 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |

*Source: Hypothetical data [Saaty, (1990)]*

**Table 2.2:** Comparison Scale

| Relative Importance of Attribute (Scale) | Definition |
|---|---|
| 1 | Equal importance (EQI) |
| 3 | Moderate importance of one over another (MI) |
| 5 | Essential or strong importance (SI) |
| 7 | Very strong importance (VSI) |
| 9 | Extreme importance (EI) |
| 2, 4, 6, 8 | Intermediate values between the two adjacent judgements (Int2, Int4, Int6, Int8) |

*Source: Hypothetical data [Saaty, (1990)]*

Saaty (2004) recommended equivalent scores from 1 to 9, as shown in Table 2.2. A preference of 1 indicates equality between two attributes, while a preference of 9 indicates that one attribute is nine times larger or more important than the attribute with which it is being compared.

2.11.2.2.1 Analytic hierarchy process procedure

According to Moore and Weatherford (2001), and as cited by Kunz (2010), there are three basic steps involved when using AHP. These steps are summarized as follows:

Step 1: Development of the weights for the criteria by

- Developing a single pair-wise comparison matrix for the criteria.
- Multiplying the values in each row together and calculating the $n^{th}$ root of said product.
- Normalizing the aforementioned $n^{th}$ root of products to get the appropriate weights.
- Calculating and checking the consistency ratio.

Step 2: Development of the ratings for each decision alternative for each criterion by

- Developing a pair-wise comparison matrix for each criterion, with each matrix containing the pair-wise comparisons of the performance of decision alternatives on each criterion.

- Multiplying the values in each row together and calculating the $n^{th}$ root of said product.
- Normalizing the aforementioned $n^{th}$ root of product values to get the corresponding ratings.
- Calculating and checking the consistency ratio.

Step 3: Calculating the weighted average rating for each decision alternative by choosing the one with the highest score.

#### *2.11.2.3 Fuzzy TOPSIS*

The technique for order of preference by similarity to ideal solution (TOPSIS) is a multi-criteria decision analysis method, which was originally developed by Hwang and Yoon in 1981, with further developments by Yoon in 1987, and Hwang, Lai and Liu in 1993. Pam (2010) in his PhD thesis cited Hwang and Yoon (1981) as alluding to the fact that TOPSIS was developed based on the concept that the chosen alternative should have the shortest distance from the positive ideal reference point (PIRP) and the farthest distance from the negative ideal reference point (NIRP). In their further work, Yoon and Hwang (1995) make the assumption that if each attribute in the decision matrix takes either a monotonically increasing or monotonically decreasing utility, it will be easier to locate the positive ideal solution, which is a combination of all the best attribute values attainable, while the negative ideal solution is a combination of all the worse attribute values attainable.

Monotonic criteria could be classified as either benefits (B) or costs (C). A criterion can be classified as a benefit if the more desirable the candidate, the higher its score versus this criterion. On the contrary, cost criteria see the least desirable candidate scoring at the lowest. In FTOPSIS, the cost criteria are defined as the most desirable candidates scoring at the lowest, while the benefit criteria are described as the most desirable candidate scoring at the highest.

Based on the work carried out by Bottani and Rizzi, (2006), TOPSIS is said to be one of the best methods in changing the rank of alternatives when a non-optimal alternative is introduced. Moreover, it is proved not to be sensitive to the number of alternatives with worst performance when dealing with a very limited number of criteria (John *et al*., 2014). TOPSIS has been applied in various fields such as: new car selection (Srikrishna *et al.,* 2014); evaluation and selection of an initial training aircraft (Wang and Chang, 2007); outsourcing of third party logistics service providers (Bottani and Rizzi, 2006); evaluation of competitive companies (Deng *et al*., 2000); the assessment of service quality in the airline industry (Tsaur *et al*., 2002); materials selection (Jee and Kan, 2000); determination of strategic priorities by SWOT analysis (Ghorbani *et al.,* 2011); and service selection (Lo *et al*., 2011 and Chao *et al.*, 2010).

According to Sodhi and Prabhakar (2012), the FTOPSIS method can help in objective and systematic evaluation of alternatives on multiple criteria. It has been demonstrated to be a robust tool for handling complex and real-life problems for collaborative modelling and decision-making processes in an uncertain environment. A fuzzy approach to TOPSIS is useful because it assigns the relative importance of attributes using fuzzy numbers instead of precise numbers. Linguistic preferences can easily be converted to fuzzy numbers and TOPSIS allows for the use of these fuzzy numbers in the calculation (Pam, 2013).

Other advantages of the FTOPSIS technique as highlighted in Bottani and Rizzi (2006), Olson (2004), and Deng *et al,* (2000) include the fact that:

1. The logic is rational and understandable.
2. Computation processes are straightforward.
3. The concept permits the pursuit of best alternatives for each criterion depicted in a simple mathematical form.
4. It allows the straight linguistic definition of weights and ratings under each criterion, without the need of cumbersome pairwise comparisons and the risk of inconsistencies.
5. The obtained weights of evaluation criteria are incorporated into the comparison procedures.

The triangular fuzzy numbers are applied in the FTOPSIS used in this study. This is because it is intuitively easy for the decision-makers to use and calculate (Dagdeviren *et al*., 2009). Secondly, modelling using triangular fuzzy numbers has proven to be an effective way to formulate the decision making problem where the information is subjective and inaccurate (Dagdeviren *et al*., 2009).

While the uncertainty issue is tackled by means of fuzzy logic, the application of TOPSIS makes it possible to appraise the distances of each decision option from the positive ideal solution and the negative ideal solution. The capability and efficiency of FTOPSIS in handling complex engineering solutions, simultaneously considering positive and negative ideal solutions, having flexibility in computational analysis, and providing systematic and logical results' evaluation, make it useful for strategic decisions to select the most ideal maintenance strategy for marine and offshore machinery. Moreover, the way linguistic ratings and weights are given is very straightforward. A Fuzzy-TOPSIS approach has been applied in this study in order to support the evaluation of decision-making criteria and attributes.

#### *2.11.2.4 Evidential Reasoning theory*

The mathematical theory of evidence was first generated by Dempster in the 1960s and later extended and refined by Shafer in the 1970s (Dempster, 1968a), (Shafer, 1976). The evidence theory was initially developed in the early 1990s to deal with multi-attribute decision making problems under uncertainty and was used to design a novel belief decision matrix that can create a unique attribute aggregation process based on the Dempster rule of combination (Fu and Yang, 2012), (Liu and Gong, 2011). The theory is widely referred to as Dempster-Shafer (D-S) theory.

The D-S evidence theory found a significant sister relationship with the Bayesian probability network (BPN) theory in the sense that, given new evidence, both can update subjective beliefs in a rational manner (Yang, *et al.,* 2006), (Shafer, 1976), (Dempster, 1968b). However, the difference between the two theories lies in the fact that the evidence theory has the capability of grouping evidence and also of dealing with ignorance in the evidence grouping process (Liu and Gong, 2011). The D-S theory was originally used for information aggregation in a complex expert system. For example, a computer system that emulates the decision-making ability of a human expert as an approximate reasoning tool (Lopez de Mantaras, 1990), (Buchanan and Shortliffe, 1984). Subsequently, it has been used in system design and operations to support decision-making under uncertainty (Yager, 1992).

There are a number of studies where ER is used. For example, Riahi (2010) used a fuzzy evidential reasoning (FER) to evaluate a seafarer's reliability; Wang and Elhang (2007) used fuzzy group decision making for bridge risk assessment; Zeng *et al.* (2006) applied an aggregative risk assessment model for information technology project development; Yang *et al.* (2005) carried out risk analysis of container supply chains using discrete fuzzy sets and an ER approach using fuzzy set theories and ER specifically on risk assessment and decision making; and Liu *et al.* (2003) used the fuzzy rule-based ER approach to analyse the safety of an engineering system with various types of uncertainties.

While MCDM is described using a decision matrix, the ER approach applies an extended decision matrix, in which each attribute of an alternative is described by a distributed assessment using a belief structure (Xu *et al.*, 2001). Each criterion is assigned with belief degrees on several linguistic evaluation grades to assess the subjective uncertainties and ambiguities associated with both quantitative and qualitative criteria. Incompleteness (or ignorance) and vagueness (or fuzziness) are among the most common uncertainties in decision analysis. Subjective judgments may be used to differentiate one alternative from another on qualitative attributes. To evaluate the quality of the operation of equipment, for example, typical judgments may be that "the condition of that equipment is poor, good, or very good to certain degrees." In such judgments, *poor, good,* and *very good* represent distinctive evaluation grades. In equipment evaluation problems, such as in a ship propulsion engine, a set of evaluation grades is defined by:

E = $\{poor\ (\beta_1)\ very\ poor\ (\beta_2)\ average\ (\beta_3)\ good\ (\beta_4)\ very\ good\ (\beta_5)\}$
where, $\beta_1, \beta_2, \beta_3, \beta_4,$ and $\beta_5$ stand for belief degrees.

The operational condition of the engine is a broad technical idea that is not easy to assess directly. The detailed components of the engine, such as piston, connecting rod, and crankshaft, *etc*. need to be considered separately to simply the assessment. If a detailed component is still too abstract to assess directly, it may be further broken down to more detailed sub-components. For instance, the piston component (y) may be measured by examining the condition of rings ($B_1$), pin ($B_2$), and skirt ($B_3$), which can be directly assessed and therefore referred to as basic attributes. Assessment attributes often constitute a multilevel hierarchy (Yang and Xu, 2002).

In hierarchical assessment, a high level attribute is assessed through associated lower level attributes. For example, if the *ring, pin,* and *skirt* of the engine piston are all assessed to be exactly *good,* then its piston should also be *good*. According to Yang and Xu (2002), when evaluating qualitative attributes, uncertain judgments can be used. For example, in assessment of the engine piston, assessors may be:

1. 30% sure that its ring is at average condition and 60% sure that it is good.
2. Absolutely sure that its pin is good.
3. 50% sure that its skirt is good and 50% sure that it is very good.

In the above assessments, 30%, 50%, 60%, and 100% (absolutely sure) are referred to as degrees of belief and can be used in decimal format as 0.3, 0.5, 0.6, and 1, respectively.

- Assessment (1) is incomplete as the total degree of belief is 0.9 (0.3 + 0.6).
- Assessments (2) and (3) are complete.
- The missing 0.1 in assessment (1) represents the degree of ignorance or uncertainty.

Difficulty can be encountered as to how to generate an overall assessment about the engine piston by aggregating the above three judgments in a rational manner. The ER approach provides a means for dealing with such an aggregation problem. The basic ER applications and algorithm are discussed in the next two subsections.

###### *2.11.2.4.1 Evidential reasoning algorithm*

ER is one of the many multiple criteria decision analysis (MCDA) methods, such as analytical hierarchy process (AHP), TOPSIS, elimination and choice expressing reality

(ELECTRE), and preference ranking organization method for enrichment evaluation (PROMETHEE). ER is applied to deal with MCDA problems for aggregating multiple criteria based on belief degree matrix (BDM) and D-S theory.

A belief degree represents the strength to which an answer is believed to be true. It must be equal to or less than 100% or it can be described as the degree of expectation that, given an alternative, it will yield an anticipated outcome on a particular criterion. The use of individual belief degrees depends on the decision makers' expertise, knowledge of the subject matter and level of experience regarding the operations of the system. The justification for the use of belief degrees is as a result of the fact that human decision making involves ambiguity, uncertainty, and imprecision where individuals make judgements in probabilistic terms aided by their knowledge.

For instance, let *S* represent a set of five condition monitoring expressions that are synthesized by two subsets, $S_1$ and $S_2$ from two different assessors. Then, $S$, $S_1$ and $S_2$ can be expressed independently as follows:

$$S = \{\beta^1 \text{"Very low"}, \beta^2 \text{"Low"},\ \beta^3 \text{"}Medium\text{"},\ \ \beta^4 \text{"High"},\ \ \beta^5 \text{"}Very\ high\text{"}\}$$

$$S_1 = \left\{{\beta_1}^1 \text{"Very low"}, {\beta_1}^2 \text{"Low"}, {\beta_1}^3 \text{"}Medium\text{"},\ \ {\beta_1}^4 \text{"High"},\ \ {\beta_1}^5 \text{"}Very\ high\text{"}\right\}$$

$$S_2 = \left\{{\beta_2}^1 \text{"Very low"}, {\beta_2}^2 \text{"Low"}, {\beta_2}^3 \text{"}Medium\text{"},\ \ {\beta_2}^4 \text{"High"},\ \ {\beta_2}^5 \text{"}Very\ high\text{"}\right\}$$

where "Very low", "Low", "Medium", "High", and "Very high" (the condition monitoring expression) are assessed with their respective degrees of belief.

If the normalised relative weights of the two assessors in the evaluation of the condition monitoring process are given by $w_1$ and $w_2$ ($w_1$ + $w_2$ = 1), then $w_1$ and $w_2$ can be estimated by using established methods such as a simple rating method or based on pair-wise comparisons (Yang *et al.,* 2001).

Suppose ${M_1}^m$ and ${M_2}^m$ (m = 1, 2, 3, 4 or 5) are individual degrees to which the subsets $S_1$ and $S_2$ support the hypothesis that the condition monitoring evaluation is confirmed to the five evaluation grades and condition monitoring expressions. Then, ${M_1}^m$ and ${M_2}^m$ can be derived as follows:

$${M_1}^m = w_1 {\beta_1}^m \ ;\ \ {M_2}^m = w_2 {\beta_2}^m \qquad (2.13)$$

where m = 1, 2, 3, 4, and 5 respectively.

$M_1{}^1 = w_1\beta_1{}^1$ ; $M_2{}^1 = w_2\beta_1{}^1$,

$M_1{}^2 = w_1\beta_1{}^2$ ; $M_2{}^2 = w_2\beta_1{}^2$,

$M_1{}^3 = w_1\beta_1{}^3$ ; $M_2{}^3 = w_2\beta_1{}^3$,

$M_1{}^4 = w_1\beta_1{}^4$ ; $M_2{}^4 = w_2\beta_1{}^4$,

$M_1{}^5 = w_1\beta_1{}^5$ ; $M_2{}^5 = w_2\beta_1{}^5$

Suppose $H_1$ and $H_2$ are the individual remaining belief values unassigned, then $H_1$ and $H_2$ can be obtained as follows (Yang and Xu, 2002):

$$H_1 = \overline{H}_1 + \widetilde{H}_1 \text{ ; } H_2 = \overline{H}_2 + \widetilde{H}_2 \tag{2.14}$$

where $\overline{H}_n(n = 1 \; or \; 2)$ represents the degree to which the other assessor can play a significant role in the assessment.

$\widetilde{H}_n(n = 1 \; or \; 2)$, causes the likely incompleteness in subsets $S_1$ and $S_2$. $\overline{H}_n \; (n = 1 \; or \; 2) \; and \; \widetilde{H}_n(n = 1 \; or \; 2)$ can be described as follows:

$\overline{H}_1 = 1 - w_1 = w_2$ ; $\overline{H}_2 = 1 - w_2 = w_1$

$$\widetilde{H}_1 = w_1\left(1 - \sum_{m=1}^{5} \beta_1{}^m\right) = \; w_1\left[1 - \left(\beta_1{}^1 + \beta_1{}^2 + \beta_1{}^3 + \beta_1{}^4 + \beta_1{}^5\right)\right] \tag{2.15}$$

$$\widetilde{H}_2 = w_2\left(1 - \sum_{m=1}^{5} \beta_2{}^m\right) = w_1\left[1 - \left(\beta_2{}^1 + \beta_2{}^2 + \beta^3{}_2 + \beta^4{}_2 + \beta_2{}^5\right)\right] \tag{2.16}$$

Suppose $\beta^{m'}$ $(m = 1, 2, 3, 4 \; or \; 5)$ represents the non-normalised degree to which the five condition monitoring expressions are confirmed as a result of the synthesis of the judgements obtained by assessors *1* and *2* respectively. Suppose $H_{U'}$ represents the non-normalised remaining belief unassigned after the commitment of belief to the five condition monitoring expressions because of the synthesis of the judgements obtained from assessors *1* and *2*. The ER algorithm can be derived as follows (Yang and Xu, 2002):

$$\beta^{m'} = K(M_1{}^m M_2{}^m + \; M_1{}^m H_2 + \; H_1 M_2{}^m) \tag{2.17}$$

$$\overline{H}_{U'} = K\left(\overline{H}_1 \overline{H}_2\right) \tag{2.18}$$

$$\widetilde{H}_{U'} = K\left(\widetilde{H}_1 \widetilde{H}_2 + \; \widetilde{H}_1 \overline{H}_2 + \; \overline{H}_1 \widetilde{H}_2\right) \tag{2.19}$$

$$K = \left[1 - \sum_{T=1}^{5} \sum_{\substack{R=1 \\ R \neq 1}}^{5} M_1{}^{T} M_2{}^{R}\right]^{-1} \tag{2.20}$$

After the above aggregation, the combined degree of belief $\beta^m$ is generated by assigning $H_{U'}$ back to the five condition monitoring expressions in the normalisation process below (Yang and Xu, 2002):

$$\beta^m = \frac{\beta^{m'}}{1-\bar{H}_{U'}}, \ (m = 1, 2, 3, 4, 5) \tag{2.21}$$

$$H_U = \frac{\tilde{H}_{U'}}{1-\bar{H}_{U'}} \tag{2.22}$$

where, $H_U$ is the unassigned degree of belief representing the level of incompleteness in the assessment. The process above highlights the sequence of combining two given sets. The algorithm can also be followed when encountering three or more sets in a hierarchical structure. If three subsets are required to be combined, the result obtained from the combination of any of the two subsets can be further synthesized with the third subset using the above algorithm. Similarly, the judgement of multiple assessors or the evaluations of the condition of the lower-level criteria in the chain systems (components or sub-components) can also be combined.

##### *2.11.2.4.2 Application of evidential reasoning*

Over the years, ER has progressively been applied to diverse multi-attribute problems (Yang, 2001), (Yang and Sen, 1997), (Wang *et al.,* 1996), (Yang and Sen, 1996), (Wang *et al.,* 1995), (Yang and Singh, 1994), and (Yang and Sen, 1994). The unique features of the ER approach have made it necessary for use in tailoring decisions that represent incomplete and fuzzy subjective judgements for machinery condition monitoring. ER has been initiated for wider application in many real-world decision making issues (Zhou *et al*., 2010). Some areas in which it has been applies include: Strategic research and development projects' assessments (Liu *et al*., 2008); Experts systems (Beynon *et al.*, 2001); Knowledge reduction (Wu *et al*., 2005); The oil reserve forecast (Zhang *et al*., 2005); Prequalifying construction contractors (Sonmez *et al*., 2002); Risk analysis (Srivastava and Liu, 2003), (Srivastava and Lu, 2002); Motor-cycle evaluation (Yang and Xu, 2002), (Yang, 2001), (Yang and Singh, 1994), (Yang and Sen, 1994); New product development (Chin *et al*., 2008); Marine system safety analysis and synthesis (Wang *et al.,* 1996), (Wang *et al.,* 1995); and General cargo ship design (Sen and Yang, 1995).

Riahi (2010) believes that in real-world decision making, ER applications have been found to have the following advantages:

- Offers a rational and reproducible methodology to aggregate data in a hierarchical evaluation process.
- Capability to provide its users with greater flexibility by allowing them to express their judgement in a subjective and quantitative manner.
- Capability to accept or represent the uncertainty and risk that is inherent in decision-making.
- Great effectiveness in processing and obtaining assessment outputs using mature computing software called Intelligent Decision System (IDS).
- Capability to handle incomplete, uncertain, and vague data as well as complete and precise data.

#### 2.11.2.5 Analysis of multiple attribute group decision making methods

MADM methods are designed to evaluate and select the desired alternative from a set of alternatives, which are characterised by multiple criteria. If more than one person is interested in the same MADM problem, it then becomes a multiple attribute group decision making (MAGDM) problem (Yang *et al.,* 2014). For both MADM and MAGDM problems, consistency among the preference relations is crucial to the result of the final decision. Guo (2013) perceives MAGDM as one of the most common activities in modern society, involving the selection of the optimal option, from a finite set of alternatives with respect to a collection of predefined criteria, by a group of experts with a high collective knowledge level on these particular criteria.

Moreover, as stated in Bozóki (2008), the determination of attribute weight is also a key issue to be considered when using the MAGDM approach. In many decision cases, some attributes are considered to be more important in the experts' judgment than the others. However, for these vital attributes, the preference relation provided by experts may be quite similar for all alternatives. Even for the attribute with the highest weight, the degree of influence on the final decision could be very small. Consequently, Wang and Fan (2007) regard this kind of attribute as being unimportant to the final decision. Thus, during the multiple attribute group decision process, the following five guidelines should be noted:

1. Different assessment types need to be considered concurrently.
2. Experts' preference relations that have been provided need to be consistent.
3. Diverse expert's opinions need to be taken into consideration.
4. The weight of each attribute needs to be determined.

5. All alternatives need to be carefully ranked.

MADM is an algorithm deployed to solve problems involving selection from a list of alternatives. It specifies how criteria or attribute information can be processed in order to arrive at a choice suitable for investment. MADM methods generally require comparisons of criteria with respect to alternatives for efficient trade-offs. In a MADM process, each decision table (also called decision matrix) has four main parts; these can be summarised as follows:

- Alternatives.
- Criteria or Attributes.
- Weight of experts or relative importance of each attribute.
- Performance measure of alternatives with respect to criteria.

Based on the analysis of MCDA methods, the basic information in a MADM model can be represented in the matrix as presented in (2.23).

$$Z = \begin{array}{c} \\ \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{matrix} C_1 & C_2 & \cdots & C_m \\ (w_1 & w_2 & \cdots & w_m) \end{matrix} \\ \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,m} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,m} \\ \vdots & \vdots & \vdots & \vdots \\ y_{n,1} & y_{n,2} & \cdots & y_{n,m} \end{bmatrix} \end{array} \tag{2.23}$$

where $A_i$ $(i = 1, 2, \ldots n)$ is the $i^{th}$ alternative; $C_i$ $(i = 1, 2, \ldots m)$ is the $i^{th}$ set of criterion with which each alternative's performances can be measured; $y_{i.j}$ $(i = 1, 2, \ldots n)$; $(j = 1, 2, \ldots m)$ is the measure of performance of the $i^{th}$ alternative with respect to the $m^{th}$ criterion; and $w_j$ $(j = 1, 2, \ldots m)$ is the $j^{th}$ criterion weight. It is important to stress here that all the elements in the decision matrix must be normalised to the same units, so that all the possible attributes in the decision problem can be dealt with easily to eliminate any computational difficulty.

There are four means of normalisation in a MADM problem (Lavasani *et al.*, 2012). The two most popular methods are summarised as follows:

- Linear Normalisation: This method divides the rating of $n$ attribute by its maximum value. Usually, the normalised value of $p_{i,j}$ can be obtained using Equation 2.24.

$$p_{i,j} = \frac{y_{i,j}}{y_j^*}, i = 1, 2, \ldots m \tag{2.24}$$

where $y_j^*$ is the maximum value of $y_{i,j}$ . $p_{i.j}$, values range between 0 to 1 $(0 \leq p_{i,j} \leq 1)$.

- Vector normalisation: This method divides the ratings of each attribute by its means square, so that each normalised rating of $y_{i,j}$ can be obtained by Equation 2.25.

$$p_{i,j} = \frac{y_{i,j}}{\sqrt{\sum_{i=1}^{n} y_{i,j}^2}}, i = 1, 2, \ldots n; j = 1, 2, \ldots m \quad (2.25)$$

Both Equations 2.24 and 2.25 are used for cost and benefit criteria respectively. Normally, an alternative in a MADM problem is often described using qualitative variables expressed by decision makers. However, when no criteria evidence or information is available, the preferred approach is to use fuzzy set theory, which has the capability of handling such a situation under varying constraints (John *et al.*, 2014).

One of the theoretical approaches to preference relations used for MADM problems is fuzzy preference relations. The majority of real-life complex problems have fuzzy information about the alternatives with respect to criteria, and it is usually difficult for crisp numerical values to be provided by the subjective opinions of decision makers due to their inadequate knowledge, and the intrinsic complexity and uncertainty within the decision-making environment. The Fuzzy Multiple Attribute Decision Making (FMADM) technique can then be used to handle these complex decision making problems, which are incomplete and unquantifiable. FMADM is an attractive approach, as it is able to actualise decision-making processes for complex equipment that has uncertainty in its operational procedures.

Hypotheses, approximations and judgments of experts are very often required in studies involving complex machinery, in order to handle the imprecision and vagueness associated with making strategic decisions about the operations of these machinery under uncertain conditions. Obviously, criteria values information is presented in the form of linguistic variables, which are generally calibrated from fuzzy scales. According to Yang *et al.* (2011), the calibration of this information from fuzzy scales is due to the fact that fuzzy logic provides the needed flexibility to represent vague information that results from a lack of data or knowledge of the piece of equipment under investigation. Therefore, there is a need for a user-friendly fuzzy decision support algorithm that can guide effective decisions in a simplified manner.

A FMCDM problem can be defined as follows:

Let $A$ = {$A_i$, for $i$ = 1, 2, 3..., *m*} be a (finite) set of decision alternatives and G = {$g_j$, for j = 1, 2, 3…, *n*} be a (finite) set of goals according to which the desirability of an action is judged. Determine the optimal alternative $A^+$ with the highest degree of desirability with respect to all relevant goals $g_j$ (Zimmermann, 1991).

According to Hipel *et al*. (1993), a decision problem is said to be complex and difficult where the following conditions apply:

1. Multiple criteria exist, which can be both quantitative and qualitative in nature.
2. There may be multiple decision makers.
3. Uncertainty and risk is involved.
4. Decision (input) data may be vague, incomplete or imprecise.

The FMCDM is applied in this model due to the fact that the decision-making process for the selection of an ideal maintenance strategy for a piece of equipment in a marine and offshore environment involves a subjective analysis of uncertain and/or incomplete data.

## 2.12 Expert System

The expert system for effective condition monitoring of marine machinery by means of oil sampling analysis is based on an understanding of the equipment, components, physical properties, and additives in the oil, as well as an understanding of the failure modes and mechanically what action needs to be taken to fix a problem.

Expert systems are very beneficial and most valuable to large organisations that have high levels of technical expertise and experience that cannot be easily transferred / shared across the business between people (Welsh, 2006). An expert system holds and maintains significant levels of information that provides consistent answers for repetitive decisions, processes, and tasks. It is a subject specific knowledge database system that contains analytical skills for knowledge management.

Generally, expert systems are made up of rules that analyse supplied information about a specific class of problems (Tyler, 2007), as well as providing diagnosis of the given problem(s) and suitable recommendations in order to implement corrections. The most important aspect of a knowledge base is the quality of information it contains; it needs to be kept up-to-date. In order to make a business secure and safe, it is ideal to have such knowledge captured in a system that can be accessible when needed, rather than in people. In this case, if the people/staff leave employment, the knowledge will be retained and accessible to others.

Highly trained professionals are still generally performing oil analysis in condition monitoring of ship cranes. The use of expert systems would allow a greater diagnostic throughput as well as enabling technicians to perform routine analysis. For multi-national companies, this will give them the opportunity to monitor performance of their lubricants and help influence their technology strategy around their products. Having a single global database is not only beneficial to achieve global business objectives but also enables the company to benchmark performance of products and applications. This therefore puts them in a very strong position when discussing how good their product is with customers and original equipment manufacturers (OEM). Furthermore, the expert system possesses great potential value for business for both laboratory and on-site maintenance operations.

### 2.12.1 Performance Thresholds

Using manufacturers' established limits and defining alerts as thresholds for the crane's performance can create effectively monitoring of the condition of the ship crane. This involves the collection and monitoring of data from the crane at each sample interval and comparing the trend against set thresholds. It is worth noting that ignoring limits or trends can have a significant impact on business performance and in some cases may invalidate the crane warranties.

Crucially, the alert limits are there to notify the responsible person that values related to precursory failure symptoms have changed in a way that is not normal – *i.e.* that are statistically remarkable (Noria Corporation, 2003). This does not necessarily mean that a failure is in progress, nor necessarily imminent, but that there has been unusual change. The person in charge should be able to understand the root cause of the change and then perform a risk analysis.

### 2.12.2 Fixed Limits

A fixed limit evaluates a simple predetermined criterion (pass or fail) for each component. The drawback to this type of technique is that it does not account for different contributing factors. For example, there are many differently sized and shaped gearboxes. Some gearboxes are lightly loaded and at constant speed, which would lend itself to a low wear rate. Such a gearbox might be in serious trouble if the iron (Fe) level were to reach 200 part per million (ppm). On the other side, there may be a low speed, reversing, and heavily loaded gearbox that has not had less than 500 ppm of iron (Fe) in its oil since it was last tested at the assembly plant.

### 2.12.3 Absolute Alarm Limit

These are limits based on manufacturers' recommendation. These alarms generally define the working ranges or condemnation limits and are most applicable to lubricant and contamination conditions. Extensive research is normally carried out to arrive at these limits, thus providing a good starting point for any analysis program. An absolute alarms limit is vital when warranties on the new equipment are of greater concern (Bots, 2014).

### 2.12.4. Trend (statistical) Alarm Limit

Manufacturers' guidelines for alarm limits or general standards are extremely poor and lacking in that they are based on average operational and performance situations, which may not precisely reflect the definite conditions of a specific machine. This is predominantly applicable to machine condition. Trend alarm limits are based on gathering a small sampling of data from equipment, analysing the distribution of that data, and using this trending characterization to set specific alarm limits (Bots, 2014). Statistical trend analysis allows the identification of the equipment in greatest need of attention, thus allocating maintenance in an efficient way. With sufficient historical data, reliable alarm limits can be established and maintained by statistical analysis.

### 2.12.5 Combination of Absolute and Statistical Alarm Limits

Effective oil analysis management relies on the combination of both types of alarm limits. The following illustration is an example of the alarm combination. The condemnation limit is the absolute alarm. Statistical trending, taking into account variability based on the sampling, contamination, make-up oil *etc.* will develop the standard deviations. Departure from this normal variability signals that real problems are taking place. This is the earliest possible time to take action. Neglecting this, as the trend approaches its warning limit, action such as changing or cleaning the oil, or inspection of the unit is required (Bots, 2014).

The idealized graph shown in Figure 2.6 is an example of how absolute and trend line alarms are used together. The test used could be on iron content, viscosity, or other parameters. The normal result variability range takes into account minor variations caused by analytical accuracy, sample homogeneity, *etc*.

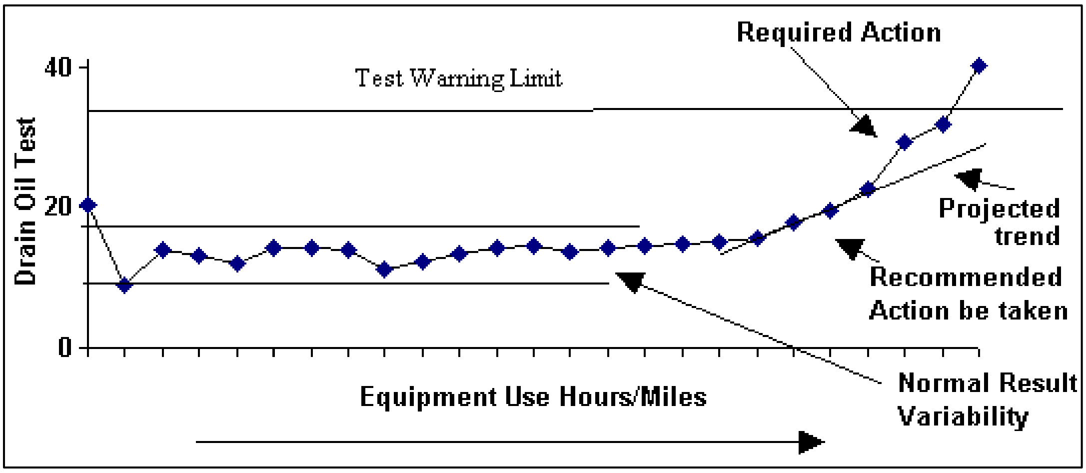


Figure 2.6: Absolute and Statistical Alarms *Source: Bently Tribology Services (n.d)*

### 2.12.6 Upper and Lower Limits

The upper limit is the value that indicates the highest level of quality acceptable for products or services, while the lower limit is the value that indicates the lowest level of quality acceptable for products or services. Both the upper control limit and the lower control limit are used in conjunction to create the range of variability for quality specifications, thus enabling experts within an organisation to provide the top level of excellence by adhering to the established guidelines.

Analysts who are familiar with the lubricants, machines, and historical problems with general reliability goals (Fitch, 1998) set the upper and the lower limits. A population mean and associated standard deviation are generated from the available data. The data from a sample is compared to the mean of the population. If the result exceeds two standard deviations, the value is considered in critical alarm as it is higher (i.e. upper), or lower as the case may be, than 95 percent of the population. Should the value exceed three standard deviations, it is a critical situation indeed, as the value exceeds the 99th percentile of the population (Fitch, 2011).

## 2.13 Conclusion

In this chapter, a systematic literature review of marine and offshore machinery operations has been presented together with relevant aspects of machinery maintenance concepts and lessons learned from major accidents in marine and offshore industry. These serve as building blocks for the development of frameworks and methodology to be used in the subsequent chapters. The current research status in maintenance planning justifies the need for further research in the field of risk-based techniques. It has convincingly revealed that a machinery maintenance programme is dependent on a number of factors including technical, operational, organisational and external issues. All these necessitate the development of a specifically tailored model that can be used to generate possible or likely failure scenarios in a straightforward manner to enhance the reliability of marine and offshore machinery operating under highly uncertain environment.

Hence, building an efficient planned maintenance strategy into these machinery systems is the next key step to assuring safety, reliability and efficiency of operations. The review of literature further revealed that collaborations with multiple stakeholders involved in marine and offshore operations would lead to good maintenance practices, which are currently much needed. The system can maximize its performance depending on the input of the correct information, be it quantitative or qualitative. Quantitative information needs to be assured and complemented by qualitative information in order to provide a convincing view of the system and propose a maintenance strategy aimed at improving the machinery operations. The literature review also revealed that the cost of maintenance is directly proportional to the ability of the maintenance system to measure its reliability. Thus, in order to implement necessary maintenance strategies, key factors need to be built into the process of group decision-making.

# Chapter 3

## Research Methodology

**Summary**

The methodology of the research carried out outlines a framework for the development of an efficient planned maintenance model for marine and offshore machinery operating under highly uncertain environments. The research integrates fuzzy set modelling and ER modelling into the maintenance model in order to improve the overall model results. The research will discuss methods of understanding a machinery maintenance process, identifying the problems encountered and establishing data that is required. This data is interpreted and parameters are then established for applying planned maintenance strategies. Further development of the maintenance model is achieved by integrating fuzzy set modelling into the rule-based model in order to improve the accuracy and level of detail of the subjective information required. The maintenance model is further expanded by integrating fuzzy set modelling into the fuzzy-TOPSIS model. This introduction serves to re-evaluate and improve a key parameter of the fuzzy-TOPSIS model.

### 3.1 The Scope of the Thesis

The scope of this research is to develop a maintenance methodology, utilising varying information from both objective and subjective sources. The purpose of the maintenance methodology is to:

a) Reduce the downtime of equipment due to breakdown and failures.
b) Reduce costs associated with maintenance and inspection activities.
c) Reduce the risks associated with possible environmental damage due to failure.

Based on the literature review in the field of machinery failure and maintenance management, the lack of research in the subject of condition-based maintenance and its effects on organisational and machinery in the context of marine and offshore industries is observed. In order to fill the gap, firstly, wider scopes of machinery failure and maintenance management that have received little attention and have been partially investigated by the researchers will be assessed. Secondly, trend, family, environmental-based, design, and human reliability will be analysed, and the influence of these five elements on the operation of machinery will be evaluated. Thirdly, a novel condition monitoring model in marine and offshore industries by employing advanced analytical methodologies will be developed. Finally, based on the evaluated results and to encounter and mitigate the evaluated risk sources and to enhance the reliability of the marine and offshore machinery, control options will be suggested.

Following the identification of the research needs and to establish an efficient condition-based maintenance and management system, a series of uncertainty methodologies such as fuzzy evidential reasoning, fuzzy analytic hierarchy process, predictive logic box (PLB), fuzzy rule-based (FRB), and multiple attribute group decision making (MAGDM) will be deployed. The frameworks of this research, in order to be applicable in marine and offshore industries, will be developed in a generic sense. To demonstrate the case studies a number of planned maintenance systems from some global companies will be selected. As a result, this research will contribute to knowledge of planned maintenance systems for the marine and offshore industries.

## 3.2 Structure of the Thesis

This thesis is compiled of seven chapters. Chapter 1 has outlined a brief introduction relating to the background of the research, an introduction of the research objectives and hypotheses, a statement highlighting the problems currently encountered.

Chapter 2 will examine the current literature which has influenced this study, giving a brief overview of current maintenance concepts as well as the marine and offshore industry in general. Following this overview, a detailed review of the current practices in maintenance planning and management, dealing with uncertainty in marine and offshore machinery design and operation, phases of errors in machinery operation, machinery oil analysis, and lessons from some major incidents in the marine and offshore industry are considered. These will serve to draw attention to the possible inadequacy and limitations of the current practices, thus demonstrating the need and justification of this research thesis. This chapter will close with a brief introduction to each of the risk-based and decision-making modelling techniques used in the thesis.

Chapter 3 discusses the methodology and scope of this thesis. It also attempts to integrate conceptual models that will be developed in Chapters 4, 5, and 6 of the research into a coherent framework that can be used for marine and offshore machinery maintenance improvement and operational management.

Chapter 4 gives a detailed and exhaustive review of what will be the cornerstone of this research thesis, fuzzy set theory (FST), analytical hierarchy process (AHP) and an aggregation algorithm (i.e. Evidential Reasoning), which are utilised to produce quantitative results that can be used by decision-makers for making robust decisions on a machinery planned maintenance management programme. This evaluation will scrutinise various applications of this modelling technique, examining some of the quantitative and qualitative information regarding machinery operations. The information includes trend analysis, family analysis, human reliability analysis, design analysis and environmental analysis. The methodology developed has been applied to a case study in order to demonstrate the process involved.

Chapter 5 looks specifically at the problems relating to the standardisation of information derived in Chapter 4 when applying fuzzy evidential reasoning sensitivity analysis model (*FER-SAM)* to a maintenance management framework. This chapter outlines the inherent problem of combining subjective judgement and objective data, and presents a powerful rule-based analysis tool fuzzy rule base sensitivity analysis model that is flexible yet robust enough to be used in a range of practical applications connected with the machinery operations.

Based on the results obtained from the analysis performed in Chapter 4, a specific model of facilitating quantitative risk analysis which integrates FST, rule based diagnosis, belief degree and mini-max concepts, with the uncertainties especially the unavailability of data is developed. This methodology has been applied to a case study in order to demonstrate the process involved. This analysis highlights the advantages of using fuzzy set modelling to elicit information from differing sources whilst overcoming the uncertainties and inaccuracies which previously surrounded this problem.

Chapter 6 generates a conceptual methodology, a strategic fuzzy decision support system for maintenance strategy selection to assist decision makers to select from the appropriate maintenance strategies suggested in Chapter 2. The methodology utilises the fuzzy multiple attribute decision-making method, which is suitable for treating group decision-making problems under a fuzzy environment. The FMADM method provides a management and engineering decisions aid in evaluating and selecting appropriate maintenance strategies from a finite number of alternatives, which are characterised by multiple attributes.

Chapter 7 will draw conclusions from the overall study. The chapter will begin by discussing the main conclusions and whether these conclusions have been addressed in this research study. This chapter will also ascertain if this research work has contributed to knowledge. The advantages and disadvantages of the models, the novel and the limitations of this research will also be given together with possible future research, which can expand and explore the body of research.

## 3.3 The Research Framework

The developed models discussed in Chapters 4, 5, and 6 using different decision-making tools, such as FST, ER, and Fuzzy Analytical Hierarchy Process (FAHP), can be integrated to develop a generic framework for an efficient planned maintenance system for marine and offshore machinery operational improvement and management. The integrated model is presented in Figure 3.1 and unveils the logical flow of the developed models in this study. The method of applying this modelling technique shows an appreciation of many elements that are generally overlooked when attempting to establish a planned maintenance schedules for particular machinery. It is this incorporation of several divergent pieces of information that establishes a cost-effective maintenance schedule, which makes maintenance analysis a potentially powerful tool for most planned maintenance frameworks.

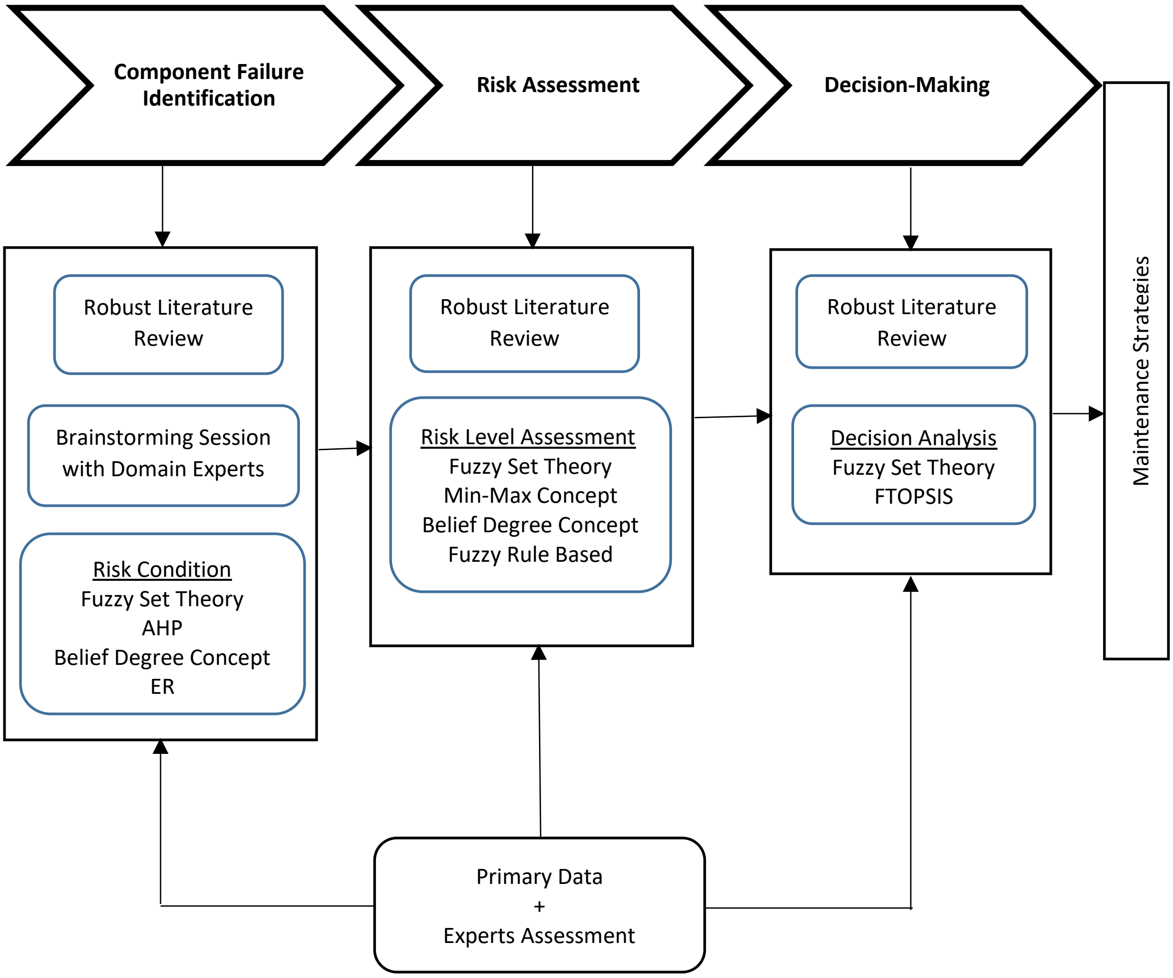


Figure 3.1: A Novel Planned Maintenance Framework for Marine and Offshore Machinery

### 3.4 Conclusion

The framework offer a transparent and systematic way to monitor the conditions of the marine and offshore machinery in a logical and straightforward manner. As revealed in this chapter, the integrated models in the framework supports maintenance management and improvement of operations more effectively than isolated processes. Moreover, the approach links maintenance and susceptibility, provides insights from different perspectives regarding the machinery’s operations, and highlights how both qualitative and quantitative information can be utilised in a transparent manner, especially in situations where data is lacking, so that machinery’s uncertainties can be revealed and addressed logically.

# Chapter 4

# A Proposed Methodology for Condition Monitoring of Marine and Offshore Machinery using Evidential Reasoning Techniques

**Summary**

This chapter will first assess the operational uncertainties of a particular piece of equipment in marine and offshore system. Trend analysis, family analysis, environmental analysis, human reliability analysis and design analysis for each criterion will be aggregated using ER and AHP algorithms. Data will be collected from reputable oil companies and supplemented by expert judgement from the related industry. The results that will be provided by these algorithms in this study will be beneficial to the marine and offshore industries as indicators for the monitoring and diagnosis of faults in machinery and thus assisting practitioners to make better decisions in their maintenance management process.

Furthermore, by changing the conditions that affect the operation of ideal machinery, and through calculating a value for this operation, a benchmark is constructed. The operational condition of machinery depends on many variables and their dependencies; thus, alteration of a criterion value will ultimately alter the operational conditions of the machinery. For any deviation to be corrected in a timely manner, the operational condition of the machinery has to be monitored properly and frequently.

## 4.1 Introduction

According to Zhao (2014), machine condition monitoring is the practice of assessing a machine's condition by periodically gathering data on key machine-health indicators to determine when to schedule maintenance. The existence or amount of debris and particles from wearing parts, erosion and contamination provide insights about the issues affecting performance and reliability. The increase in failure of marine and offshore machinery, such as main engines, cranes, pumps, *etc*., coupled with intense operator concern over their reliability, has motivated this research and the development of an efficient condition monitoring methodology and reliability procedures. Furthermore, with the increasing complexity and cost of equipment, accurate diagnosis is important. As a result, Classification Societies are putting pressure on marine and offshore companies, urging them to streamline their machinery condition monitoring operations. The fundamental element of machinery condition monitoring on-board ship is watch-keeping (Lloyd Register, 2013). Watch-keeping involves the ability to recognize changes in performance, as indicated by alarms, alerts, gauges and readings, as well as responding aptly to these changes. However, as the industry becomes more dynamic, there is a need to introduce concepts of flexibility and agility (Bastos *et al.*, 2012), to enable companies to deliver customized condition monitoring (CM) which can react swiftly to machinery operating in highly uncertain environments.

In their normal day-to-day schedules, deck and engineering officers do carry out many condition monitoring activities, such as monitoring the performance of individual components in a piece of equipment. For example, some of the routine condition monitoring activities carried out in marine vessels include the installation of temperature sensors in cylinder liners to monitor piston rings blow-by, and visual inspection of piston rings and liners through scavenge space (Lloyd Register, 2013).

Thus, within this chapter, the framework of monitoring and diagnosing machinery in marine and offshore industries will be demonstrated. ER and AHP algorithms will be employed to synthesise the data gathered from all the components, in what is called a *data mining process* (DMP). This will identify the behaviour patterns of each component, thus allowing more accurate early detection of faults in the equipment.

The structure of this chapter will be as follows. The second section presents the process of building a generic model of a hierarchical structure for monitoring the condition of the machinery, in which trend, family, environment, human reliability, and design analysis information is processed. The methodology is then explained and applied to the monitoring of the operational conditions of machinery in the third section. This proposed methodology, along with a previously accepted condition monitoring methodology, is then tested by a case study, followed by a discussion and conclusion.

## 4.2 Methodology

The procedures specified in the literature review that were found to be considerable in their relationships to machinery condition monitoring are used as the basis of the generic model. The condition of the equipment is evaluated using a combination of different decision making techniques, such as AHP, ER, and data mining process utilizing expert judgements and historical data from the relevant industry. The proposed methodology will assess the operational condition of different components in a piece of equipment to ascertain which components are prone to failure. The proposed methodology in a stepwise regression is presented in the following sections. The flow diagram for evaluating the condition of equipment is shown in Figure 4.1.

### 4.2.1 Identification of Risk Criteria (Step one)

It is very important for the decision makers to fully understand and have a clear picture of the whole problem before attempting to find a solution, especially when there are many criteria that need to be considered, which may in turn consist of sub-criteria and sometimes even sub-sub-criteria. In such situations, the problem can be displayed in the form of a hierarchical structure. Using hierarchical order, the goal of the problem is indicated at the first level, while in the second level, there are several criteria, each of which contribute to measuring and helping to achieve the overall goal. Then some of these criteria can further be broken down. This process can continue up to the point where the decision makers are able to make practical evaluation. When constructing a hierarchical structure, it is important to pay attention to only significant criteria, in order to avoid a superfluously large model size.

Based on the literature review of the condition monitoring of the marine and offshore machinery, a generic model with a hierarchical structure is constructed, and the main criteria, sub-criteria, and sub-sub-criteria that contribute to the condition monitoring of the machinery (goal) are presented in Figure 4.2. The goal (E) of the condition monitoring is stated in the first level. In the second level, the main criteria ($C_1$, $C_2$, $C_3$ and $C_4$) contributing to the condition monitoring of the goal (E) are stated. Then in the third level, the sub-criteria {($C_{11}$, $C_{12}$, $C_{13}$,), ($C_{21}$, $C_{22}$, $C_{23}$), ($C_{31}$, $C_{32}$, $C_{33}$), ($C_{41}$, $C_{42}$, $C_{43}$)} contributing to the condition monitoring of the main criteria and the goal are stated. Then finally, in the fourth level, sub-sub-criteria showing different contributions to measuring and achieving the goal of the problem are stated. However, this can be further broken down into sub-criteria sub-sub-sub-criteria until a point where decision makers can make practical and informed decisions on the lower level criteria.

### 4.2.2 Application of Analytic Hierarchy Process (Step two)

Analytical Hierarchy Process (AHP) is used to determine the weights of each risk factor by conducting a pair-wise comparison. Triangular fuzzy numbers (TFNs) are used to calculate the preference of one criterion over another because of their computational simplicity in promoting representation of information in an uncertain environment. The comparison is usually based on an estimation scheme which places intensity of importance using qualitative variables. Each of the variables has a corresponding TFN that is employed to transfer experts' judgement into a corresponding matrix.

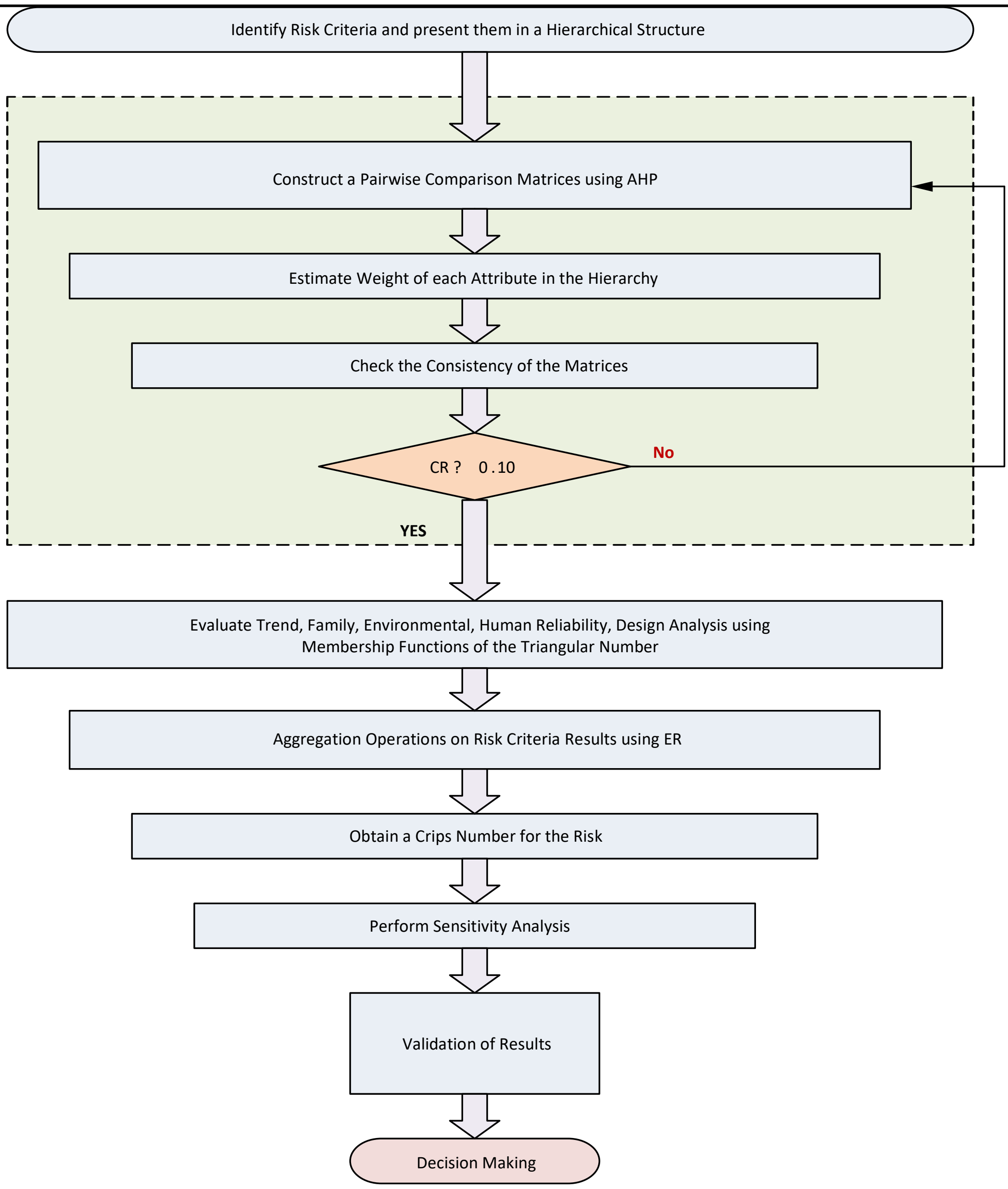


Figure 4.1: Flow diagram for evaluating the condition of equipment

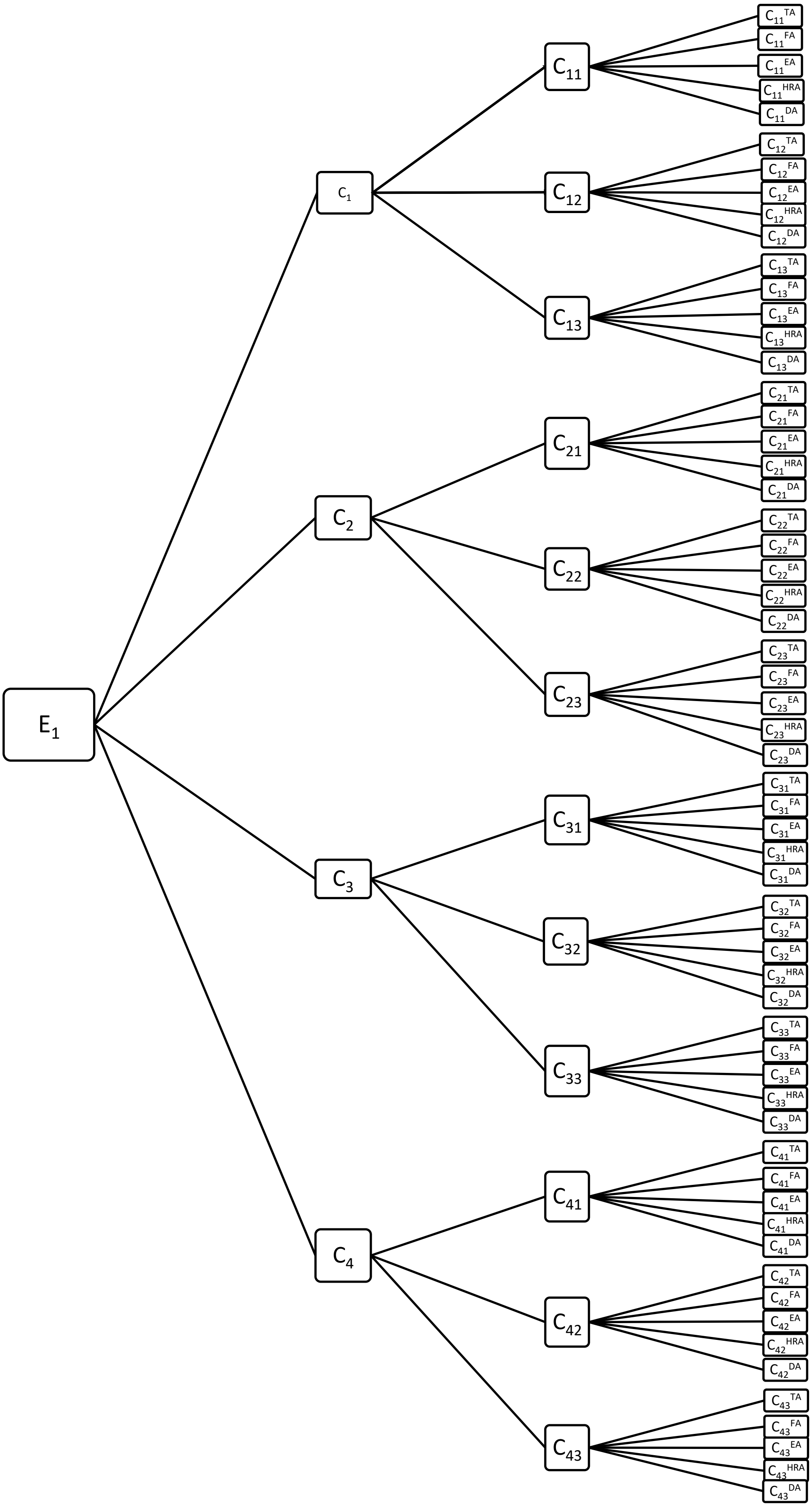


**Figure 4.2 - A Generic Model for Condition Monitoring of Machinery**

#### 4.2.2.1 Experts composition

Table 4.1 indicates the position, service time and the qualifications of the experts used for the survey.

**Table 4.1:** Composition of Experts

| Composition | Classification |
|---|---|
| Industry Position | Senior Manager |
| Service Time | > 30 years |
| Academic Qualification | ▪ Master degree<br>▪ Bachelor degree<br>▪ HND<br>▪ Class 1 Certificate of Competency |

### 4.2.3 Evaluation of Trend Analysis (TA) (Step three)

Trend analysis is an aspect of technical analysis that tries to predict the future performance of machinery based on past data recorded. It is centred on the idea that what has happened in the past gives an idea of what will happen in the future. Trend analysis allows the development of a pattern of behaviour for a particular unit. This pattern of behaviour may develop within a short or long term period. In trend analysis, graphs of a condition-related parameter versus time can be utilized to determine when the parameter is likely to exceed a given limit. This time could be dates or running hours.

The goal of a successful condition monitoring program is to predict the time of an expected breakdown well in advance of its occurrence in order to shut down the machine in ample time and allow for the ordering of spare parts for repairs, thus minimizing the shutdown time. According to Courrech and Eshleman (2014), all condition monitoring criteria indicate that equal changes on a log scale correspond to equal changes in severity; therefore, data for a trend analysis should be plotted on a logarithmic scale in decibels. A linear trend on a logarithmic scale is found occasionally, but the actual trend may follow another path; for example, when the fault feeds back on the rate of deterioration (e.g. gear wear), the trend, when plotted on a logarithmic scale, may then be exponential. In some cases, the fault changes suddenly in finite steps, making it very difficult to extrapolate the time of the shutdown. An example is a spall caused by gradual subsurface fatigue.

The following precautions are very vital in ensuring that accurate trend analysis is being obtained (Courrech and Eshleman, 2014):

1. Determining a trend based on measurements of a parameter directly related to a specific type of fault, not on measurements of overall levels.
2. Diagnosing faults before attempting to interpret a trend curve in order to:
   a) Select the appropriate parameter for the type of fault that is being monitored. For example, the parameter may be the level of an individual component, or of a selected frequency range.
   b) Observe critically the results of the trend analysis so as to determine if the linear or exponential interpolation is adequate.
3. Employing a trend of the most recent measurements to obtain the best estimate of the lead time.

Several techniques can be applied in evaluating trend data, such as standard deviations, averages, linear regression, *etc*. All of these techniques are intended to identify a condition that is not normal in relation to the equipment's past behaviour. In this research, trend analysis is evaluated by means of quantitative data transformation (QDT). Each quantitative criterion (i.e. grease/oil sample element test result) is transformed to a qualitative criterion (i.e. linguistic variables with the associated belief degree) by using the triangular membership functions of continuous fuzzy sets.

#### 4.2.4 Evaluation of Family Analysis (Step four)

Family Analysis compares the results (e.g. wear metal levels) of groups of similar or identical machinery to identify the usual or typical pattern. The extraction of such information provides the data necessary to characterize operating cycles, maintenance schedules, periodic breakdowns, and most importantly, to identify and address abnormal failure rates before critical problems arise. In many cases, systems are grouped together to form a family. A family may consist of identical equipment located in one or many vessels. Equipment can also be grouped together based on: load, size, lubrication type, and operating parameters, such as a group of pumps on-board a vessel. In this way, the wear metal data can then be evaluated as a whole. The data for each component can then be compared to the family to evaluate its wear rate to the family (Clarke 2005).

In family analysis, component patterns are classified to obtain component groups, and machine patterns are also classified to machine groups. The machine component matrix is arranged by placing components within a component group adjacently and repeating the same for machines. The resulting matrix can then be inspected for bottleneck machines and the number of exceptional cells can be minimized. Comparable to the similarity coefficient in similarity coefficient methods, a degree of similarity between the obtained pattern and the ideal pattern is used. The similarity is measured to ensure whether the obtained pattern is properly classified or not (Dagli *et al*., 1995). However, when determining the family analysis of two similar systems, the similarity is compared with a pre-specified threshold. A different threshold can be specified for the classification of components and machines. From there a different degree of clustering is obtained for each threshold (as in the similarity coefficient method).

Clark (2005) opines that family analysis techniques can have a significant impact on both large and small companies' condition monitoring programmes. A large company can use such a programme to monitor large fleets of similar equipment among their plants, as well as benchmark the performance of individual plants. Conversely, a company with less equipment can use family analysis techniques to compare their equipment wear rates with equipment in many other plants, or taking advantage of the vast laboratory database of equipment data for comparison.

The family analysis is also evaluated using a quantitative data transformation method. Unlike the trend analysis, in which only one deck crane was considered, in family analysis, two deck cranes (Port & Starboard) are being evaluated by calculating the standard deviations of the test results from the laboratory for each of the criterion (element). Each quantitative criterion is then transformed to a qualitative criterion by using triangular membership functions of continuous fuzzy sets. To move from inaction to action required status, standard deviations are calculated to reveals whether the failure modes under review are very similar and the standard deviation is low and predictable, using the following formula:

$$\text{Standard Deviation} = \sqrt{\frac{\sum(x - \bar{x})^2}{(n-1)}} \tag{4.1}$$

where $x$ is the sample mean average and $n$ is the sample size.

### 4.2.5 Evaluation of Environmental Analysis (Step five)

The health and performance of machinery as a whole is vitally important. Rather than focusing on the performance of one part, analysts look at everything together in order to obtain a more complete view of what is achievable and what problems might arise along the way. When machinery operators have comprehensive views of their internal and external environments, they are often better able to plan an effective growth strategy. At the same time, early threat identification allows operators to take timely action in developing a survival plan and setting remediation plans in motion to get the machinery back to good condition.

Environmental analysis evaluates the environmental conditions under which the machinery is currently operating. Environmental conditions will be based on vibration measurement, velocity, and acceleration. However, in the current situation, there is no system to collect the data regarding the environmental conditions of the components involved. Good environmental analysis depends on a constant stream of pertinent information (Camponovo, *et al.,* n.d). In view of this, the test case will be handled in different types of environment, as suggested.

### 4.2.6 Evaluation of Human Reliability Analysis (Step six)

Human reliability is related to the field of human factors and ergonomics. As it is common today, human is a crucial part of the large socio-technical systems. Thus, human reliability is very significant due to the contributions of humans to the resilience of systems and to possible adverse consequences of human errors or oversights. Human reliability analysis (HRA) will assess the operator's performance during the machinery operations practice. According to MAIB (2010), human error is a factor in the majority of marine machinery failures. Psaraftis *et al.*'s (2000) analysis of maritime accident reports indicated that most of the accidents had a human factor as the prevalent cause.

Researchers have done several studies to evaluate human reliability. Riahi *et al.* (2012) assessed the reliability of a seafarer incorporating subjective judgement; in their assessment, Riahi *et al.* (2012) present a dynamic model capable of coping with changing conditions that affect the performance of a seafarer. Adams (1982) analysed the issues affecting human reliability; Askren (1967) evaluated the reliability of human performance in work; Meister (1964) produced a method of predicting human reliability in man machine systems; and Swain (1963) produced a method for performing a human factors reliability analysis. Given that extensive research works on evaluation of human reliability have been conducted by many researchers and experts, the test case on HRA will rely extensively on the results obtained by Riahi *et al.* (2012) from their assessment and evaluation of a seafarer's reliability.

### 4.2.7 Evaluation of Design Analysis (Step seven)

Machinery and equipment for shipboard use is designed to operate successfully under severe condition. Ship machinery systems incorporate all the on-board machinery that is used for propulsion, manoeuvring, cargo handling, fresh water production, space heating, etc. This set of equipment constitutes the ship's energy conversion systems, often referred to as the marine energy system (Kakalis *et al.,* 2012). These marine energy systems are designed to convert the chemical energy of the fuel (lubricants) to the forms required to be used in shipboard, and they tend to be highly complex, having many functions, with variable mission profiles, as well as requirements for flexibility, redundancy, and safety. In addition, the systems have to be cost-effective, energy efficient, and environmental friendly. In order to manage such complexity, it is imperative to adopt a structured and effective approach during the design phase.

Design Analysis will assess the physical behaviour of the machinery and its component as specified by the manufacturer (good or bad). It is based on the prediction of the physical behaviour of just about any part or assembly, under any loading condition. In a safe design, the load is not excessive, the stress does not exceed the yield point (i.e. the type of material used operates within its elastic range or limit), and the part deforms elastically (i.e. when the load is released, the part returns to its original shape). On the other hand, if the load is such that the yield point is exceeded, the part will become partially plastic and, on removal of the load, the part will be permanently deformed. Subsequently, greater increase in load will cause the part to eventually break (fracture). This is normally attributed to bad design.

### 4.2.8 Aggregation Operations on Criteria Results Using ER (Step eight)

The ER algorithm is used to synthesise the risks in a hierarchical structure. Complex decision making problems are represented hierarchically in a structured and systematic manner, as constructed in the generic model shown in Figure 4.2. In order to find how well an alternative performs across all criteria, the lowest level criteria evaluation is transformed to the upper level and ultimately to the top level criterion. This complex process requires a robust and systematic decision making tool and ER is a method that can be tailored towards such situations where there is high uncertainty and imprecision in information processing. With the help of ER, the results obtained from the AHP and the criteria are aggregated.

### 4.2.9 Obtaining a Crisp Number for the Goal (Step nine)

To obtain a single crisp number for the top-level criterion (goal) of each alternative, a utility approach is used in order to rank them. If the utility of an evaluation grade $H_n$ is denoted by $u(H_n)\ and\ u(H_{n+1})\ > u(H_n)$, where $H_{n+1}$ is preferred to $H_n$, $u(H_n)$ can be estimated using the decision maker's preferences. However, in a situation where no preference information is available, it could be assumed that the utilities of evaluation grades are equidistantly distributed in a normalised utility space. The utilities of evaluation grades that are equidistantly distributed in a normalised utility space are calculated as follows:

$$u(H_n) = \frac{V_n - V_{min}}{V_{max} - V_{min}} \tag{4.2}$$

where, $V_n$ is the ranking value of the linguistic term $H_n$ that has been considered, $V_{max}$ is the ranking value of the most-preferred linguistic term $H_N$, and $V_{min}$ is the ranking value of the least-preferred linguistic term $H_1$.

The utility of the top-level or general criterion $S(E)$ is denoted by $u\big(S(E)\big)$. If $\beta_H \neq 0$ (i.e. the assessment is incomplete, $\beta_H = 1 - \sum_{n=1}^{N} \beta_n$) there is a belief interval $[\beta_{n,} (\beta_n + \beta_H)]$, which provides the likelihood that $S(E)$ is assessed to $H_n$. Without loss of generality, suppose that the least-preferred linguistic term having the lowest utility is denoted by $u(H_1)$ and the most preferred linguistic term having the highest utility is denoted by $u(H_N)$. Then according to Yang (2001), the minimum, maximum, and average utilities of $S(E)$ are defined as:

$$u_{min}\big(S(E)\big) = \sum_{n=2}^{N} \beta_n\, u(H_n) + (\beta_1 + \beta_H) u(H_1)$$

$$u_{min}\big(S(E)\big) = \sum_{n=1}^{N-1} \beta_n\, u(H_n) + (\beta_N + \beta_H) u(H_N)$$

$$u_{average}\big(S(E)\big) = \frac{u_{min}\big(S(E)\big) + u_{max}\big(S(E)\big)}{2} \tag{4.3}$$

If all the assessments are complete, then $\beta_H = 0$ and the maximum, minimum, and average utilities of $S(E)$ will be the same. Therefore, $u\big(S(E)\big)$ can be calculated as:

$$u\big(S(E)\big) = \sum_{n=1}^{N} \beta_n\, u(H_n) \tag{4.4}$$

According to Riahi *et al.* (2012), an assessment based on a single value is much easier and more instinctive as a practical tool for a professional decision maker to rank the alternative. Thus, to obtain a single crisp number for the goal, the utility value associated with each linguistic term has to be calculated from Equations (4.2) to (4.4).

### 4.2.10 Perform Sensitivity Analysis (Final step)

It is humanly impossible to define a condition monitoring strategy that has every potential failure covered and it is equally very challenging to have good statistical data which reveals that the failure modes under review are very similar and the standard deviation is low and predictable. As a result, owing to the lack of precise data and the novelty of this model, it has not been possible to find any proven benchmark results for its full validation. Given such difficulties and challenges, a possible method for fully validating the model can be achieved only by using an incremental process and through conducting more industrial case studies. The model that will be developed can then be refined and applied in real-world industrial applications.

In view of the above, sensitivity analysis will be used to partially validate the model. The reason for using sensitivity analysis is to test the sensitivity of the proposed model. Sensitivity analysis refers to analysing how sensitive the model outputs are to a minor change in the inputs. The change may be a variation in the parameters of the model or may be changes in the belief degrees assigned to the linguistic variables used to describe the parameters. Sensitivity analysis is very useful when attempting to determine the impact the actual outcome of a particular variable will have if it differs from what was previously assumed. By forming a given set of scenarios, how changes in one variable(s) will impact the target variable can be determined. If the methodology is sound and its conclusion reasoning is logical, then the sensitivity analysis must follow the following three axioms (Riahi *et al.,* 2012):

Axiom 1: A slight increment or decrement in the degree of belief associated with any linguistic variables of the lowest-level criteria will certainly result in a relative increment or decrement in the degree of belief of the linguistic variable and the preference degrees of the model output.

Axiom 2: If the degree of belief associated with the highest-preference linguistic term of the lowest-level criterion is decreased by $m$ and $n$, simultaneously the degree of belief associated with its lowest-preference linguistic term is increased by $m$ and $n$ ($1 > n > m$), and the utility values of the model output are evaluated as $U_m$ and $U_n$ respectively, then $U_m$ should be greater than $U_n$.

Axiom 3: If $S$ and $R$ ($R < S$) criteria from all the lowest-level criteria are selected and the degree of belief associated with the highest-preference linguistic term of each of such $S$ and $R$ criteria is decreased by the same amount (i.e. simultaneously the degree of belief associated with the lowest-preference linguistic term of each of such $S$ and $R$ criteria is increased by the same amount) and the utility values of the model output are evaluated as $U_R$ and $U_S$ respectively, then $U_R$ should be greater than $U_S$.

The implementation of the axioms will help to test the certainty of the delivery of the analysis result. The degrees of belief associated with the highest preference linguistic terms of each sub-criterion are decreased by $k$ and simultaneously, the degrees of belief associated with the lowest preference linguistic terms of the corresponding sub-criterion are increased by

$k$. Thus, the corresponding results are obtained. It is worth noting that when the belief degree of the highest preference linguistic term $\beta_\alpha$ of a criterion is decreased by $k$, simultaneously, the belief degree of its lowest preference linguistic term has to be increased by $k$. However, if $\beta_\alpha$ is less than $k$, then the remaining belief degree (i.e. $k - \beta_\alpha$) can be taken from the belief degree of the next linguistic term. This process continues until $k$ is consumed (Riahi *et al.*, 2012). The comparative ship crane reliability (SCR) results obtained from this methodology are used to determine which crane's components are susceptible to failure. The component with a low SCR value is identified as the one more prone to failure.

### 4.3 Test Case

In order to investigate the possibility of failure throughout the lifespan of a ship crane (Figure 4.3) and during its operations, it is essential to monitor the conditions of its components (main criteria) in terms of their reliability during frequently changing sea conditions, by evaluating the laboratory oil sample test results for these components based on the given absolute limits for oil. The operating condition of both port and starboard cranes in an oil tanker operating within European nautical environments is evaluated based on the following information. Furthermore, the disparity in their conditions during frequently changing sea conditions is calculated. The characteristics of the cranes, the intended use, type, and size of the vessel, and the environment are listed as follows:

1. Crane type: DONG Nam hydraulic crane on main deck – 10 Ton.
2. Offshore crane used in floating production storage and offloading (FPSO).
3. Crane arrangement: Port and Starboard.
4. Degree of rotation: $350^0$.
5. Environmental operating conditions: extremes temperature -$20^0$C to +$45^0$C.
6. Personnel allowed to be lifted with the crane.
7. The crane has an operator's cabin.
8. Lift Height/Depth: 1200m depth double fall.
9. Overload alarm: set to 100% of SWL.
10. The crane has the following main components: slewing rings bearing, clutches, gearboxes, and hydraulic pumps. Regular oil sample analysis is carried out for these components, and their laboratory test results are recorded.
11. Using a crane for tasks outside its design intent can significantly increases safety risks, crane failures, and downtime. Consequently, the manufacturer, taking into account indication of the design loads, life, and estimated average running time, evaluated the overall design of the crane as Good.

### 4.3.1 Ship Crane Machinery

Cranes are fitted on board most ships and offshore installations for cargo handling and lifting of personnel. These cranes appear to be fairly robust units which will continue to work when only a minimum of maintenance is carried out. They are highly complex pieces of machinery that incorporate numerous components manufactured to very fine tolerances, all of which must function correctly throughout a working period of the crane, as a unit, to be operated as the manufacturers recommended. The machinery of a crane includes all electrical control equipment and systems, motors, hydraulic oil pumps, filters and coolers, winches, clutches, brakes and control gear, limit switches, bearings and other pieces of equipment. Routine maintenance of these various pieces of machinery is essential for their continuing correct operation.

In accordance with the planned maintenance regime, inspections and testing of the various parts should be carried out, with renewal of items as necessary. If any component is not in the appropriate good condition, failures are likely to occur during cargo operations. In this study, only the four key components (bearing, clutches, gearboxes and hydraulic pump) will be considered in the maintenance model in order for simplify the model.


Figure 4.3: Dongnam Hydraulic Crane on FPSO Main Deck

### 4.3.2 Slewing ring bearings

Slewing ring bearings shown in Figure 4.4 are commonly used in marine cranes for transferring/supporting axial, radial, and moment loads, singularly or in combination. They consist of rings mounted with threaded fasteners, usually with a gear integral with one of the rings. The slew bearing, which is a main structural load-bearing device that attaches the crane to the vessel, is a potential source for catastrophic failure. There are many instances in which cranes have been detached from the vessel because of failure in the slewing bearing.

Figure 4.4: Crane Slewing Bearing

The lubricants normally recommended by slewing ring bearing manufacturers are greases or oil bath lubrication for slowly rotating continuous operating enclosed bearings, where adequate sealing of the bearing enclosure exists (Rezmireş *et al.*, 2010). Grease in itself may be defined as the lubricant that is in a solid or semi-solid state and contains thickener, and some various special additives.

### 4.3.3 Gearboxes

Marine crane gearboxes are expected to perform under conditions of high heat and heavy loads. In environments often contaminated with dirt, process debris, and water, without adequate protection, gears will wear prematurely and replacement of parts would need to be done more frequently. Oil change would also need to be done more often, and worst of all, would experience equipment downtime. To combat these difficult conditions, well-formulated lubricants have to be used in marine gearbox applications (Lubrication Engineers, n.d).

Gear oil is made up of two critical components: base oil and additives. Additives impart desirable properties and suppress undesirable ones. The additive package is the backbone of the lubricant's performance, and a strong backbone will provide the performance and protection needed for the gearbox. When selecting gear oil, there are three essential attributes to consider:

1. The gear oil must remain thermally stable and not oxidize at high temperatures, thus avoiding the creation of sludge or varnish. Keeping the oil from oxidizing will lengthen drain and replacement intervals. As a general rule of thumb, for every 18 degrees F (10 degrees C) increase in fluid temperature above 140°F (60°C), oxidation will reduce the service life of a lubricant by half.
2. The gear oil must have extreme pressure properties. Gear oil with an extreme pressure (EP) additive will protect the gear surfaces against extreme pressures.
3. Gear oil must fight contamination that enters the system, especially water. The oil must be able to demulsify, which allows for easy removal of the water from the gearbox.

Figure 4.5: Crane Gearbox

### 4.3.4 Clutches

Figure 4.6 shows hydraulically actuated marine crane clutches and brakes which work exclusively with “wet-running” oil-cooled plates with the friction pairing steel/sintered lining. The advantages of actuation with pressure oil at 80 bar, the multi-plate construction type and the oil-cooled friction pairing steel/high-performance sinter result in an exceptionally compact design with high performance. It features high torques, low mass moments of inertia, high switch times and little maintenance. Since they run in a sealed housing, no dirt is released into the environment.

Proper lubrication with only qualified lubricants is the prerequisite for achievement of highest efficiency and long life of high quality clutches. Only with use of oil or grease lubricants specified by the manufacturer. The amount of grease should cover approximately 60% of the free volume in the clutch. Care should be taken for homogene dispersion of the grease all over the clutch.

Figure 4.6: Crane Clutch

### 4.3.5 Hydraulic Pump

In all this wide variety of machinery, hydraulics plays a very vital role. The hydraulic technology is so precise and accurate that they are used in the main engine control and manoeuvring systems, deck cranes, winches, etc. The purpose of the ship crane is to stay stable whilst lifting heavy weights. The hydraulic pump is therefore, use in generating the necessary pressure that allow the crane to remain stabled during operations. The application of hydraulic oil pressure and operation of respective valves control the flow of hydraulic oil and enable the crane to perform the required operation. Figure 4.7 shows a crane hydraulic pump having a flow rate of 40 Lpm to 250 Lpm15.8.

Figure 4.7: Crane Hydraulic Pump

### 4.3.6 Identification of Risk Criteria (Step one)

When a group of similar components contributes to a common goal or function, grouping of such components facilitates their analysis. Hence, the introduction of a hierarchical model into the machinery system allows for an effective way to deal with the complexity associated with its operation in order to reveal its uncertainties. The hierarchical structure highlights the interaction among the components and determines how they perform together as a whole to contribute to the goal of the entire piece of machinery.

Considering the generic model for monitoring the condition of the machinery (Figure 4.2) and the above information, a specific model (Figure 4.8) for monitoring the condition of a ship crane can be constructed. Analysis grades are assigned to all the criteria in the hierarchical structure and the qualitative and quantitative criteria are grouped. Four main criteria (bearing, clutch, gearbox, and hydraulic pump) and five sub-criteria (trend analysis, family analysis, environmental analysis, human reliability analysis, and design analysis) are identified for the ship crane.

### 4.3.7 Application of Analytic Hierarchy Process Results (Step two)

Questionnaires were sent to four experts (listed in Table 4.2) in the industry carefully selected to participate in the analysis with the aim of comparing the nine criteria (four main criteria and five sub-criteria) that are perceived in the condition monitoring of marine and offshore cranes. These nine criteria are set up in order of importance, by employing an analytic hierarchy process to determine their priority ranking for decision making. The nine criteria are used in four crane components: bearing, clutch, gearbox, and hydraulic pump. The decision maker determines the rating for each decision alternative for each criterion. The ratings for expert 1's judgements are used as an example to show how the weights (priority vector) are determined. Then afterward, the ratings for the four experts' judgement will be aggregated using the AHP software and the results will be shown. There will be one pair-wise comparison matrix for each criterion. Then, within each matrix, the pair-wise comparisons will rate each sub-criterion relative to every other sub-criterion.

#### 4.3.7.1 Selected experts and their assigned weights

The experts' background in the industry and their assigned weights are as shown in Table 4.2.

**Table 4.2:** Weighting of Expert Judgments

| Number of Decision Makers | Industrial Position | Service Period | Academic Qualification | Experts' Weights |
|---|---|---|---|---|
| DM1 | Senior Manager | > 30 years | Master | 0.25 |
| DM2 | Senior Manager | > 30 years | HND | 0.25 |
| DM3 | Senior Manager | > 30 years | Bachelor | 0.25 |
| DM4 | Senior Manager | > 30 years | Class 1 Certificate of Competency | 0.25 |
| | | | | **Total = 1** |

4.3.7.2 Development of the ratings for each decision alternative for each criterion

Based on the five sub-criteria identified, five separate matrices have been developed accordingly: one matrix for the trend analysis, one matrix for the family analysis, one matrix for the environmental analysis, one matrix for the human reliability analysis, and one matrix for the design analysis. Within each of the aforementioned five matrices, there will be pair-wise comparisons for each component against every other component relative to that criterion. Since there are five sub-criteria under evaluation, each matrix will be of size 5 x 5. Table 1-4A in Appendix 4A indicates the Expert 1 judgement in comparing the five criteria for crane bearing, while Table 4.3 shows the pair-wise comparison matrix for the five criteria from Expert 1.

From Table 1-4A (Appendix 4A), the Expert 1 determines that for the crane bearing:

1. Trend analysis is strongly important over family analysis (number 5).
2. Trend analysis is strongly to very strongly important over environmental analysis (number 6).
3. Trend analysis is very strongly important over human reliability analysis (number 7).
4. Trend analysis is strongly to very strongly important over design analysis (number 6).
5. Family analysis is equally to weakly important over environmental analysis (2).
6. Family analysis is strongly important over Human reliability analysis (5).
7. Family analysis is equally important over design analysis (1).
8. Environmental analysis is weakly important over human reliability analysis (3).
9. Design analysis is strongly important over environment analysis (5).
10. Design analysis is strongly important over human reliability analysis (5).

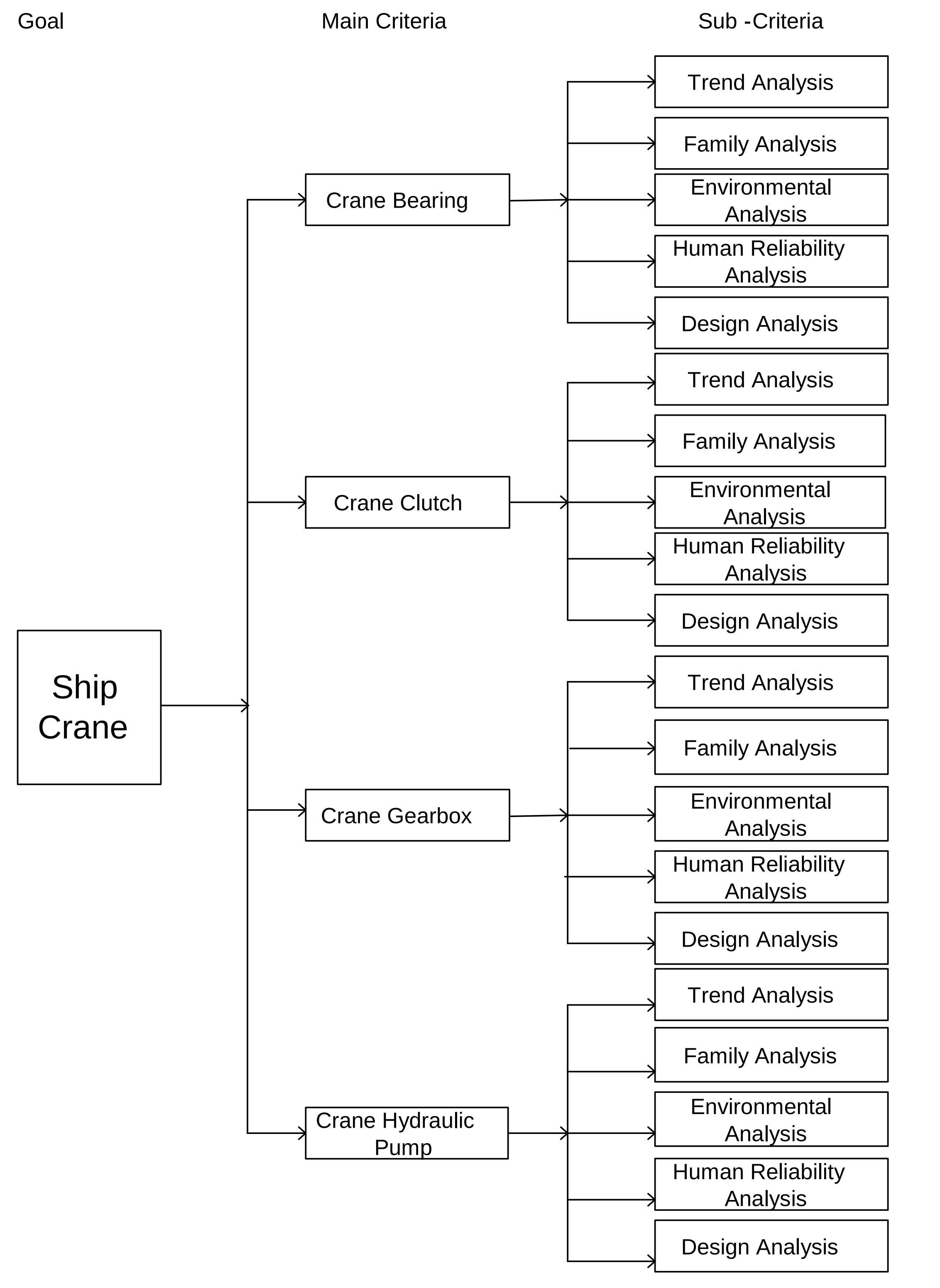


Figure 4.8: Specific Model for Condition Monitoring of a Ship Crane

With the aforementioned pair-wise comparison values, a pair-wise comparison matrix can be constructed. Then the weights for trend analysis, family analysis, environmental analysis, human reliability analysis, and design analysis are computed. The 5 x 5 matrix in Table 4.3 contains all of the pair-wise comparisons for the criteria. The "equally important" values shown along the upper left to lower right diagonal are comparing each criterion to itself and so, by definition, must be equal to one.

The remaining values shown in the matrix represent the reciprocal pair-wise comparison of relationships previously mentioned.

From Table 4.3, the values in each row are multiplied together and the fifth root of the sub-criteria is calculated as follows:

TA: $(1 \times 5 \times 6 \times 7 \times 6)^{(1/5)} = 4.169$

FA: $(0.2 \times 1 \times 2 \times 5 \times 1)^{(1/5)} = 1.149$

EA: $(0.167 \times 0.5 \times 1 \times 3 \times 0.2)^{(1/5)} = 0.549$

HRA: $(0.143 \times 0.2 \times 0.333 \times 1 \times 0.2)^{(1/5)} = 0.286$

DA: $(0.167 \times 1 \times 5 \times 5 \times 1)^{(1/5)} = 1.331$

**Table 4.3:** Expert 1 Pair-wise Comparison Matrix for the Five Criteria

| Crane Bearing | TA | FA | EA | HRA | DA |
|---|---|---|---|---|---|
| **TA** | 1 | 5 | 6 | 7 | 6 |
| **FA** | 0.2 | 1 | 2 | 5 | 1 |
| **EA** | 0.167 | 0.5 | 1 | 3 | 0.2 |
| **HRA** | 0.143 | 0.2 | 0.333 | 1 | 0.2 |
| **DA** | 0.167 | 1 | 5 | 5 | 1 |

*Source: Test case data*

The fifth root of the sub-criteria values (and total) from the previous steps is normalized to obtain the appropriate weights (priority vector) for each criterion. The weights for each criterion are calculated as follow:

TA: (4.169 / 7.484) = 0.557

FA: (1.149 / 7.484) = 0.154

EA: (0.549 / 7.484) = 0.073

HRA: (0.286 / 7.484) = 0.038

DA: (1.331 / 7.484) = 0.178

The priority vector (PV) values are the criteria weights. The weights for each criterion must sum to one (i.e. the total priority vector), as shown in Table 4.4.

**Table 4.4:** Developing Expert 1 Rating for each Decision Alternative for the Crane Bearing

| Crane Bearing | TA | FA | EA | HRA | DA | 5th Root of Component | PV |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 6 | 7 | 6 | 4.169 | 0.557 |
| FA | 0.2 | 1 | 2 | 5 | 1 | 1.149 | 0.154 |
| EA | 0.167 | 0.5 | 1 | 3 | 0.2 | 0.549 | 0.073 |
| HRA | 0.143 | 0.2 | 0.333 | 1 | 0.2 | 0.286 | 0.038 |
| DA | 0.167 | 1 | 5 | 5 | 1 | 1.331 | 0.178 |
| SUM | 1.677 | 7.7 | 14.333 | 21 | 8.4 | 7.484 | **1.000** |
| SUM * PV | 0.934 | 1.186 | 1.046 | 0.798 | 1.495 | **5.459** | |
| Lambda-max = 5.459 | | | | | | | |
| CI = 0.115 | | | | | | | |
| CR = 0.103 | | | | | | | |

*Source: Test case data*

The pair-wise comparison values in each column are added together (as the "sum" values) and each sum is then multiplied by the respective weight (from the priority vector column) for those criteria, as follows:

TA: (1 + 0.2 + 0.167 + 0.143 + 0.167) x 0.557 = 0.934

FA: (5 + 1 + 0.5 + 0.2 + 1) x 0.154 = 1.1858

EA: (6 + 2 + 1 + 0.333 + 5) x 0.073 = 1.046

HRA: (7 + 5 + 3 + 1 + 5) x 0.038 = 0.798

DA: (6 + 1 + 0.2 + 0.2 + 1) x 0.178 = 1.495

In the row labelled "Sum*PV" shown in Table 4.4, each value shows the result of multiplying the respective sum (shown in the row immediately above) by the respective weight for that criterion (shown in the column labelled "priority vector").

The aforementioned values (shown in the row labelled "Sum*PV") are added together to yield a total of 5.459 (i.e., 0.934 + 1.186 + 1.046 + 0.798 + 1.495 = **5.459**). This value is called *Lambda-max*. Note that unlike the weights for the criteria, which must sum to one, Lambda-max will not necessarily be equal to one.

Using Equation (2.11), the consistency index (CI) is calculated as:

CI = (Lambda-max – n) / (n-1); where n = 5

CI = (5.459 – 5) / (5-1) = 0.459 / 4 = **0.115**

The CR is calculated by dividing the consistency index (CI) by a random index (RI), which is determined from a lookup table in Table 2.1. The RI is a direct function of the number of criteria or components being considered. Using Equation (2.10), CR is calculated as:

CR = CI / RI

The number of sub-criteria being considered in this test case is 5, thus, from Table 2.1, RI for 5 is given as 1.12.

CR = 0.115 / 1.12 = **0.103**

If the CR $\leq$ 0.10, the decision maker's pair-wise comparisons are relatively consistent. In this case, the CR is 0.10, which indicates that the pair-wise comparisons are consistent and no correction action is necessary.

Note that the CR for the matrix in Table 4.4 depicting the ratings for each decision alternative for each criterion is less than or equal to 0.10, meaning that the pair-wise comparisons are relatively consistent. Therefore, no further actions are necessary.

The ratings for Expert 2, 3 and 4 for crane bearing are as shown in Appendix 4A; Tables 2-4A, 4-4A, and 6-4A, and their corresponding pair-wise comparisons are shown in Tables 3-4A, 5-4A, and 7-4A respectively.

Their corresponding CR are found to be less than or equal to 0.10, thus depicting that their pair-wise comparisons are also consistent. Similarly, the ratings and the pair-wise comparisons of the individual four experts for the remaining three components (clutch, gearbox, and hydraulic pump) and their corresponding CR are obtained and shown in Tables 8-4A to 31-4A in Appendix 4A.

#### 4.3.7.3 Combining the four experts' judgement to determine the pair-wise comparison matrix for each decision alternative for each criterion

Considering the ratings from the four experts for the crane bearing, as shown in Appendix 4A, Tables 1-4A, 2-4A, 4-4A and 6-4A, by applying Equation (2.8) and similar techniques used in Section 4.3.7.2, their value ratings can be combined to determine their pair-wise comparison values for the crane bearing, as shown in Table 4.5.

Let $e_1$, $e_2$, $e_3$, and $e_4$ represent Experts 1, 2, 3, and 4 respectively.

TA: FA = $(e_1 \times e_2 \times e_3 \times e_4)^{1/4}$ = $(5 \times 3 \times 5 \times 5)^{1/4}$ = 4.4

TA: EA = $(6 \times 1 \times 5 \times 4)^{1/4}$ = 3.31

TA: HRA = $(7 \times 6 \times 5 \times 2)^{1/4}$ = 4.527

TA: DA = $(6 \times 4 \times 5 \times 0.5)^{1/4}$ = 2.783

FA: TA = $(0.2 \times 0.33 \times 0.2 \times 0.2)^{1/4}$ = 0.226

FA: EA = $(2 \times 0.5 \times 0.33 \times 0.33)^{1/4}$ = 0.574

FA: HRA = $(5 \times 6 \times 3 \times 2)^{1/4}$ = 3.663

FA: DA = $(1 \times 6 \times 1 \times 0.33)^{1/4}$ = 1.186

EA: TA = $(0.167 \times 1 \times 0.2 \times 0.25)^{1/4}$ = 0.302

EA: FA = $(0.5 \times 2 \times 3 \times 3)^{1/4}$ = 1.732

EA: HRA = $(3 \times 6 \times 3 \times 1)^{1/4}$ = 2.711

EA: DA = $(0.2 \times 2 \times 1 \times 0.33)^{1/4}$ = 0.603

HRA: TA = $(0.143 \times 0.166 \times 0.2 \times 0.5)^{1/4}$ = 0.220

HRA: FA = $(0.2 \times 0.166 \times 0.33 \times 0.5)^{1/4}$ = 0.272

HRA: EA = $(0.333 \times 0.166 \times 0.333 \times 1)^{1/4}$ = 0.368

HRA: DA = $(0.2 \times 0.25 \times 0.333 \times 0.25)^{1/4}$ = 0.254

DA: TA = $(0.167 \times 0.25 \times 0.2 \times 2)^{1/4}$ = 0.359

DA: FA = $(1 \times 0.167 \times 1 \times 3)^{1/4}$ = 0.841

DA: EA = $(5 \times 0.5 \times 1 \times 3)^{1/4}$ = 1.655

DA: HRA = $(5 \times 4 \times 3 \times 4)^{1/4}$ = 3.936

**Table 4.5:** Combined Pair-Wise Comparison Matrix for Crane Bearing

| **Crane Bearing** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root** | **PV** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 4.4 | 3.31 | 4.527 | 2.783 | 2.836 | 0.484 |
| FA | 0.226 | 1 | 0.574 | 3.663 | 1.186 | 0.562 | 0.096 |
| EA | 0.302 | 1.732 | 1 | 2.711 | 0.603 | 0.969 | 0.165 |
| HRA | 0.220 | 0.272 | 0.368 | 1 | 0.254 | 0.354 | 0.060 |
| DA | 0.359 | 0.841 | 1.655 | 3.936 | 1 | 1.144 | 0.195 |
| SUM | 2.107 | 8.245 | 6.907 | 15.837 | 5.826 | 5.865 | **1.000** |
| SUM * PV | 1.019 | 0.791 | 1.139 | 0.950 | 1.136 | **5.035** | |
| Lambda-max = 5.035 | | | | | | | |
| CI = 0.087 | | | | | | | |
| CR = 0.077 | | | | | | | |

*Source: Test case data*

Similarly, considering the experts' ratings in Tables 8-4A, 10-4A, 12-4A, 14-4A, 16-4A, 18-4A, 20-4A, 22-4A, 24-4A, 26-4A, 28-4A, and 30-4A, the four experts' combined pair-wise comparison values for the crane clutch, gearbox, and hydraulic pump are obtained as shown in Tables 4.6, 4.7, and 4.8 respectively.

**Table 4.6:** Combined Pair-Wise Comparison Matrix for Crane Clutch

| **Crane Clutch** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root** | **PV** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 3.344 | 4.606 | 5.144 | 4.949 | 3.301 | 0.503 |
| FA | 0.299 | 1 | 1.778 | 3.499 | 0.841 | 1.094 | 0.167 |
| EA | 0.217 | 0.562 | 1 | 1.861 | 0.379 | 0.612 | 0.093 |
| HRA | 0.193 | 0.286 | 0.537 | 1 | 0.293 | 0.387 | 0.059 |
| DA | 0.203 | 1.189 | 2.632 | 3.409 | 1 | 1.167 | 0.178 |
| SUM | 1.912 | 6.381 | 10.553 | 14.913 | 7.462 | 6.561 | **1.000** |
| SUM * PV | 0.962 | 1.066 | 0.981 | 0.879 | 1.328 | **5.216** | |
| Lambda-max = 5.216 | | | | | | | |
| CI = 0.054 | | | | | | | |
| CR = 0.05 | | | | | | | |

*Source: Test case data*

**Table 4.7:** Combined Pair-Wise Comparison Matrix for Crane Gearbox

| **Crane Gearbox** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root** | **PV** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 4.729 | 4.729 | 6.117 | 4.162 | 3.557 | 0.524 |
| FA | 0.212 | 1 | 1.861 | 4.401 | 1 | 1.117 | 0.165 |
| EA | 0.212 | 0.537 | 1 | 2.059 | 0.595 | 0.674 | 0.099 |
| HRA | 0.163 | 0.228 | 0.485 | 1 | 0.255 | 0.341 | 0.050 |
| DA | 0.239 | 1 | 1.682 | 3.936 | 1 | 1.096 | 0.162 |
| SUM | 1.826 | 7.494 | 9.757 | 17.513 | 7.012 | 6.785 | **1.000** |
| SUM * PV | 0.957 | 1.237 | 0.966 | 0.876 | 1.136 | **5.172** | |
| Lambda-max = 5.172 | | | | | | | |
| CI = 0.043 | | | | | | | |
| CR = 0.04 | | | | | | | |

*Source: Test case data*

**Table 4.8:** Combined Pair-Wise Comparison Matrix for Crane Hydraulic Pump

| **Crane Hydraulic Pump** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root** | **PV** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 4.472 | 4.229 | 3.873 | 3.761 | 3.076 | 0.485 |
| FA | 0.224 | 1 | 1.732 | 4.162 | 1.189 | 1.139 | 0.181 |
| EA | 0.236 | 0.577 | 1 | 2.449 | 0.904 | 0.787 | 0.124 |
| HRA | 0.258 | 0.239 | 0.408 | 1 | 0.302 | 0.377 | 0.059 |
| DA | 0.265 | 0.841 | 1.107 | 3.309 | 1 | 0.960 | 0.151 |
| SUM | 1.983 | 7.129 | 8.476 | 14.793 | 7.156 | 6.339 | **1.000** |
| SUM * PV | 0.962 | 1.290 | 1.051 | 0.873 | 1.081 | **5.257** | |
| Lambda-max | = 5.257 | | | | | | |
| CI | = 0.064 | | | | | | |
| CR | = 0.057 | | | | | | |

*Source: Test case data*

#### 4.3.7.4 Weight assignment

In order to show the relative important of each sub-criterion for its associated main criterion, it is necessary to assign a weight to each sub-criterion (TA, FA, EA, HRA and DA). Four experienced experts with equal weights have judged and evaluated the relative importance of specific sub-criterion for their associated main criterion (i.e. crane bearing, clutch, gearbox, and hydraulic pump).

**Table 4.9.** Weights of the Sub-Criteria

| Sub-Criteria | Crane Bearing | Crane Clutch | Crane Gearbox | Crane Hydraulic Pump |
|---|---|---|---|---|
| Trend Analysis | 0.484 | 0.503 | 0.524 | 0.485 |
| Family Analysis | 0.096 | 0.167 | 0.165 | 0.181 |
| Environmental Analysis | 0.165 | 0.093 | 0.099 | 0.124 |
| Human Reliability Analysis | 0.060 | 0.059 | 0.050 | 0.059 |
| Design Analysis | 0.195 | 0.178 | 0.162 | 0.151 |

*Source: Test case data*

Considering the four experts' pair-wise comparison matrix of the five attributes (sub-criteria) for the main criteria, as shown in Tables 4.5 to 4.8, and based on Equations (2.9) to (2.12), the CR is calculated as 0.1 and the weight of the five attributes are assessed as shown in Table 4.9.

### 4.3.8 Evaluation of Trend Analysis (Step three)

Evaluation of trend analysis for the four main criteria (bearing, clutch, gearbox and hydraulic pump) is carried out by transforming the grease sample element test results from the crane bearing and the oil sample element test results from the clutch, gearbox, and hydraulic pump to a linguistic variable with the associated belief degree using triangular membership functions of continuous fuzzy sets. This is illustrated in subsequent sections. Individual test elements are described utilizing five linguistic terms: *Very Low*, *Low, Average*, *High* and *Very Hig*h. The explanation of the linguistic terms describing individual scenario is given in Table 4.10.

**Table 4.10:** Description for Test Elements and General Interpretation

| Linguistic Term for Test Elements | General Interpretation |
|---|---|
| Very Low | Wear particles present in small quantities. Acceptable amount of normal wear particles. |
| Low | Wear particles present in small quantities. Acceptable amount of normal wear particles. |
| Average | Wear particles present in medium quantities. Acceptable amount of normal wear particles. |
| High | Wear particles present in high quantities. Unacceptable amount of normal wear particles. |
| Very High | The wear metals content is higher than normal. The crane should be stopped for investigation. |

*Source: Test case data*

#### *4.3.8.1 Evaluation of trend analysis for the crane bearing*

Table 4.11 shows the laboratory test results obtained for grease samples taken from the port crane slewing bearing of a FPSO, while Table 4.12 shows the absolute limits for a crane bearing used grease sample obtained from a reputable oil company. In order to evaluate the trend analysis for this port crane bearing, each of the grease element test results listed in Table 4.11, with their corresponding limit in Table 4.12, is transformed to linguistic variable with associated belief degrees. For example:

*Iron (Fe) element in bearing grease samples:*

Based on experts' opinions, the upper limit is found and the rules are written for iron (Fe) element with equal distributions, demonstrated as follows:

1. If a crane bearing grease sample laboratory test has a result of 100ppm iron (Fe) or lower, then it can be categorised as 100% Very Low.
2. If a crane bearing grease sample laboratory test has a result of 200ppm iron (Fe), then it can be categorised as 100% Low.
3. If a crane bearing grease sample laboratory test has a result of 300ppm iron (Fe), then it can be categorised as 100% Average.
4. If a crane bearing grease sample laboratory test has a result of 400ppm iron (Fe), then it can be categorised as 100% High.
5. If a crane bearing grease sample laboratory test has a result of 500ppm iron (Fe) and above, then it can be categorised as 100% Very High.

Based on the above rules, the membership functions of the iron (Fe) can be constructed as shown in Figure 4.10.

**Table 4.11:** Grease Sample Report for Ship Port Crane Bearing

| Elements | Sample 3 | Sample 2 | Sample 1 |
|---|---|---|---|
| Iron (Fe) mg/kg | 43 | 20 | 27 |
| Chromium (Cr) mg | 0 | 0 | 5 |
| Molybdenum (Mo) | 0 | 0 | 0 |
| Tin (Sn) mg/kg | 15 | 0 | 0 |
| Lead (pb) mg/kg | 45 | 5 | 14 |
| Copper (Cu) mg/k | 122 | 0 | 14 |
| Sodium (Na) mg/k | 84 | 59 | 0 |
| Magnesium (Mn) m | 0 | 24 | 0 |
| Nickel (Ni) mg/k | 5 | 1 | 72 |
| Aluminium (Al) m | 13 | 22 | 174 |
| Silicon (Si) mg/k | 8 | 51 | 30 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 4.12:** Absolute Limits for Crane Bearing Used Grease Sample

| Test | Upper Attention | Upper Action |
|---|---|---|
| Iron (Fe) | 500 | 750 |
| Chromium (Cr) | 8 | 11 |
| Molybdenum (Mo) | 40 | 50 |
| Tin (Sn) | 40 | 60 |
| Lead (Pb) | 15 | 20 |
| Copper (Cu) | 15 | 20 |
| Sodium (Na) | 150 | 200 |
| Magnesium (Mg) | 90 | 100 |
| Nickel (Ni) | 5 | 8 |
| Aluminium (Al) | 90 | 150 |
| Silicon (Si) | 150 | 250 |

*Source: Hypothetical data from a reputable lubricants manufacturer*

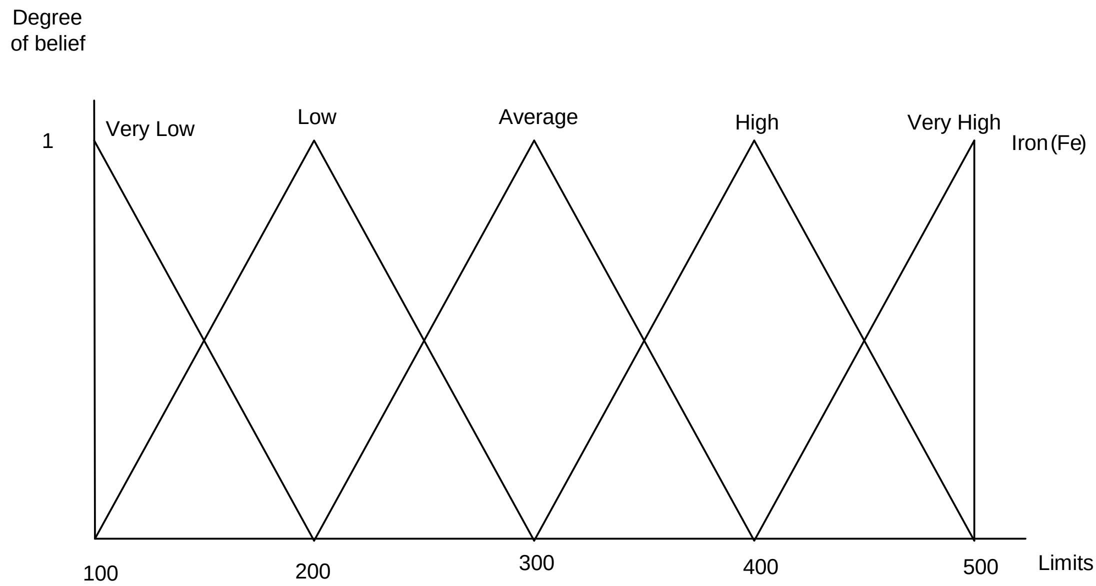

Figure 4.9: Membership Function of the Iron (Fe) Element – Trend Analysis

Based on the stated rules and by viewing the iron (Fe) contents for the crane bearing grease test results as an independent criterion, the iron (Fe) contents of 20ppm to 43ppm indicate that the crane bearing is still in good condition. Thus, 20ppm to 43ppm iron (Fe) contents in a grease crane bearing can be categorised as 100% Very Low.

Based on the information in Table 4.11, the laboratory test result for grease sample 1 indicates iron (Fe) contents of 27ppm. Based on Figure 4.9 and Equation (2.6), the belief degrees are calculated as follows:

$H_{n+1}$ is the Very Low grade; $h_{n+1,i} = 100$

$h_i$ = 27, 27 < 100

Thus, based on rule 1, the iron (Fe) contents in grease sample 1 test result set are assessed as:

$\widetilde{Fe}_1$ **= {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}**

In the similar way, the iron (Fe) contents in grease samples 2 and 3 test result sets are assessed as:

$\widetilde{Fe}_2$ **= {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}**

$\widetilde{Fe}_3$ **= {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}**

Using a similar technique, based on expert opinions, the upper limit is found and the rules for other elements are demonstrated. Based on the given rules, membership functions for the elements are constructed as shown in Figures 1-4B1 to 11-4B1, Appendix 4B1. Based on the information in Table 4.11, the laboratory test results set for samples 1, 2, and 3 are assessed and their corresponding belief degrees are calculated and recorded as shown in Table 4.13. Thus, with the help of the ER algorithm, the trend analysis for the fuzzy set of crane bearing grease samples 1, 2 and 3 are conducted and the results shown in Table 4.13.

#### 4.3.8.2 Evaluation of trend analysis for the crane clutch

Table 4.14 shows the laboratory test results obtained for the oil samples taken from the port crane clutch, while Table 4.15 shows the absolute limits for the crane clutch used oil sample.

Applying the same techniques described in Section 4.3.8.1, and based on the information in Tables 4.14 and 4.15, the membership functions of the elements in the crane clutch oil samples 1, 2 and 3 are constructed and shown in Figures 1-4B2 to 9-4B2, Appendix 4B2. Trend analysis for the fuzzy set of crane clutch oil samples 1, 2 and 3 is conducted and the results are shown in Table 4.16.

#### 4.3.8.3 Evaluation of trend analysis for the crane gearbox

Table 4.17 shows the laboratory test results obtained for the oil samples taken from the port crane gearbox, while Table 4.18 shows the absolute limits for the crane used gearbox oil sample.

In a similar way, and based on the information in Tables 4.17 and 4.18, the membership functions of the elements in the crane gearbox oil samples are constructed as shown in Figures 1-4B3 to 12-4B3, Appendix 4B3. Trend analysis for the fuzzy set of crane gearbox oil samples 1, 2 and 3 is conducted and the results are shown in Table 4.19.

**Table 4.13**: Fuzzy Sets for Crane Bearing Grease Samples – Trend Analysis

| Test Elements | Fuzzy Sets for Sample 1 | Fuzzy Sets for Sample 2 | Fuzzy Sets for Sample 3 |
|---|---|---|---|
| Iron (Fe) | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Chromium (Cr) | {(0, Very Low), (0, Low), (0.875, Average), (0.125, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Tin (Sn) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.125, Very Low), (0.875, Low), (0, Average), (0, High), (0, Very High)} |
| Molybdenum (Mo) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}, | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}, | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}, |
| Lead (Pb) | {(0, Very Low), (0, Low), (0, Average), (0.33, High), (0.67, Very High)} | {(0.33, Very Low), (0.67, Low), (0, Average), (0, High), (0, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} |
| Copper (Cu) | {(0, Very Low), (0, Low), (0, Average), (0.33, High), (0.67, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} |
| Sodium (Na) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.03, Very Low), (0.97, Low), (0, Average), (0, High), (0, Very High)} | {(0, Very Low), (0.2, Low), (0.8, Average), (0, High), (0, Very High)} |
| Magnesium (Mg) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.66, Very Low), (0.34, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Nickel (Ni) | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} |
| Aluminium (Al) | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} | {(0.77, Very Low), (0.23, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Silicon (Si) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.3, Very Low), (0.7, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| **Aggregation Result** | **{(0.5858, Very Low), (0, Low), (0.0664, Average), (0.0611, High), (0.2867, Very High)}** | **{(0.7828, Very Low), (0.2172, Low), (0, Average), (0, High), (0, Very High)}** | **{(0.6041, Very Low), (0.0831, Low), (0.0609, Average), (0, High), (0.2519, Very High)}** |

*Source: Test case data*

**Table 4.14:** Grease Sample Report for Ship Port Crane Clutch

| Elements | Sample 3 | Sample 2 | Sample 1 |
|---|---|---|---|
| Iron (Fe) mg/kg | 6 | 8 | 8 |
| Chromium (Cr) mg | 0 | 0 | 0 |
| Molybdenum (Mo) | 0 | 0 | 0 |
| Tin (Sn) mg/kg | 1 | 0 | 1 |
| Lead (Pb) mg/kg | 1 | 1 | 2 |
| Copper (Cu) mg/k | 5 | 6 | 5 |
| Aluminium (Al) m | 1 | 0 | 0 |
| Silicon (Si) mg/k | 4 | 5 | 4 |
| Vanadium (V) mg/k | 9 | 10 | 8 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 4.15:** Absolute Limits for Crane Clutch Oil Tests

| Test | Upper Attention | Upper Action |
|---|---|---|
| Iron (Fe) | 45 | 68 |
| Chromium (Cr) | 5 | 8 |
| Molybdenum (Mo) | 6 | 8 |
| Tin (Sn) | 10 | 15 |
| Lead (Pb) | 5 | 11 |
| Copper (Cu) | 22 | 32 |
| Aluminium (Al) | 10 | 15 |
| Silicon (Si) | 35 | 55 |
| Vanadium (V) | 40 | 53 |

*Source: Hypothetical data from a reputable lubricants manufacturer*

**Table 4.16:** Fuzzy Sets for Crane Clutch Oil Samples – Trend Analysis

| Test Elements | Fuzzy Sets for Sample 1 | Fuzzy Sets for Sample 2 | Fuzzy Sets for Sample 3 |
|---|---|---|---|
| Iron (Fe) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Chromium (Cr) | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Molybdenum (Mo) | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Tin (Sn) | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Lead (Pb) | {(0, Very Low), (1, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Copper (Cu) | {(0.86, Very Low), (0.14, Low), (0, Average), (0, High), (0, Very High)} | {(0.64, Very Low), (0.36, Low), (0, Average), (0, High), (0, Very High)} | {(0.86, Very Low), (0.14, Low), (0, Average), (0, High), (0, Very High)} |
| Aluminium (Al) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Silicon (Si) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Vanadium (V) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.75, Very Low), (0.25, Low), (0, Average), (0, High), (0, Very High)} | {(0.875, Very Low), (0.125, Low), (0, Average), (0, High), (0, Very High)} |
| **Aggregation Result** | **{(0.9134, Very Low), (0.0866, Low), (0, Average), (0, High), (0, Very High)}** | **{(0.9562, Very Low), (0.0438, Low), (0, Average), (0, High), (0, Very High)}** | **{(0.9818, Very Low), (0.0182, Low), (0, Average), (0, High), (0, Very High)}** |

*Source: Test case data*

**Table 4.17:** Oil Sample Report for Ship Port Crane Gearbox

| Test Elements | Sample 3 | Sample 2 | Sample 1 |
|---|---|---|---|
| Water Content %v | 0.1 | 0 | 0 |
| Total Acid Number (TAN) | 0.31 | 0.42 | 0.37 |
| Iron (Fe) mg/kg | 13 | 11 | 15 |
| Chromium (Cr) mg | 0 | 0 | 0 |
| Molybdenum (Mo) | 187 | 259 | 513 |
| Tin (Sn) mg/kg | 3 | 0 | 22 |
| Lead (Pb) mg/kg | 0 | 0 | 0 |
| Copper (Cu) mg/k | 31 | 29 | 36 |
| Sodium (Na) mg/k | 0 | 3 | 0 |
| Aluminium (Al) m | 4 | 3 | 6 |
| Silicon (Si) mg/ | 4 | 4 | 9 |
| Vanadium (V) mg/ | 0 | 0 | 0 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 4.18:** Absolute Limits for Crane Gearbox Oil Tests

| Test | Upper Attention | Upper Action |
|---|---|---|
| Water Content | 0.1 | 0.21 |
| Total Acid No. (TAN) | 1.5 | 2.5 |
| Iron (Fe) | 60 | 98 |
| Chromium (Cr) | 4 | 6 |
| Molybdenum (Mo) | 6 | 9 |
| Tin (Sn) | 7 | 9 |
| Lead (Pb) | 28 | 47 |
| Copper (Cu) | 36 | 60 |
| Aluminium (Al) | 7 | 10 |
| Silicon (Si) | 30 | 40 |
| Sodium (Na) | 30 | 40 |
| Vanadium (V) | 5 | 10 |

*Source: Hypothetical data from a reputable lubricants manufacturer*

**Table 4.19:** Fuzzy Sets for Crane Gearbox Oil Samples – Trend Analysis

| Test Elements | Fuzzy Sets for Sample 1 | Fuzzy Sets for Sample 2 | Fuzzy Sets for Sample 3 |
|---|---|---|---|
| Water Content | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} |
| TAN | {(0.76, Very Low), (0.24, Low), (0, Average), (0, High), (0, Very High)} | {(0.6, Very Low), (0.4, Low), (0, Average), (0, High), (0, Very High)} | {(0.96, Very Low), (0.04, Low), (0, Average), (0, High), (0, Very High)} |
| Iron (Fe) | {(0.75, Very Low), (0.25, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.92, Very Low), (0.08, Low), (0, Average), (0, High), (0, Very High)} |
| Chromium (Cr) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Molybdenum (Mo) | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} |
| Tin (Sn) | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0, Very Low), (0.85, Low), (0.15, Average), (0, High), (0, Very High)} |
| Lead (Pb) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Copper (Cu) | {(0, Very Low), (0, Low), (0, Average), (0, High), (1, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0.97, High), (0.03, Very High)} | {(0, Very Low), (0, Low), (0, Average), (0.69, High), (0.31, Very High)} |
| Aluminium (Al) | {(0, Very Low), (0, Low), (0, Average), (0.71, High), (0.29, Very High)} | {(0, Very Low), (0.85, Low), (0.15, Average), (0, High), (0, Very High)} | {(0, Very Low), (0.14, Low), (0.86, Average), (0, High), (0, Very High)} |
| Silicon (Si) | {(0.5, Very Low), (0.5, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Sodium (Na) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Vanadium (V) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| **Aggregation Result** | **{(0.6331, Very Low), (0.0694, Low), (0, Average), (0.0484, High), (0.2491, Very High)}** | **{(0.7812, Very Low), (0.0816, Low), (0.0096, Average), (0.0618, High), (0.0658, Very High)}** | **{(0.6298, Very Low), (0.079, Low), (0.0713, Average), (0.0482, High), (0.1717, Very High)}** |

*Source: Test case data*

### 4.3.8.4 Evaluation of trend analysis for the crane hydraulic pump

Table 4.20 shows the laboratory test results obtained for the oil samples taken from the port crane hydraulic pump, while Table 4.21 shows the absolute limits for the crane used hydraulic pump oil sample.

**Table 4.20**. Oil Sample Report for Ship Port Crane Hydraulic Pump

| Test Elements | Sample 3 | Sample 2 | Sample 1 |
|---|---|---|---|
| Water Content %v | 0 | 0 | 0 |
| Iron (Fe) mg/kg | 0 | 0 | 1 |
| Chromium (Cr) mg | 0 | 0 | 0 |
| Molybdenum (Mo) | 0 | 0 | 0 |
| Tin (Sn) mg/kg | 0 | 0 | 0 |
| Lead (Pb) mg/kg | 0 | 0 | 0 |
| Copper (Cu) mg/k | 0 | 9 | 7 |
| Sodium (Na) mg/k | 0 | 9 | 0 |
| Aluminium (Al) m | 0 | 0 | 0 |
| Silicon (Si) mg/ | 0 | 0 | 0 |
| Vanadium (V) mg/ | 0 | 0 | 0 |

Source: Hypothetical data from a reputable oil test laboratory

**Table 4.21**. Absolute Limits for Crane Hydraulic Pump Oil Tests

| Test | Upper Attention | Upper Action |
|---|---|---|
| Water Content | 0.2 | 0.5 |
| Iron (Fe) | 23 | 36 |
| Chromium (Cr) | 6 | 10 |
| Molybdenum (Mo) | 6 | 10 |
| Tin (Sn) | 6 | 10 |
| Lead (Pb) | 8 | 13 |
| Copper (Cu) | 36 | 55 |
| Sodium (Na) | 30 | 40 |
| Aluminium (Al) | 6 | 10 |
| Silicon (Si) | 30 | 35 |
| Vanadium (V) | 5 | 10 |

*Source: Hypothetical data from a reputable lubricants manufacturer*

**Table 4.22:** Fuzzy Sets for Crane Hydraulic Pump Oil Samples – Trend Analysis

| Test Elements | Fuzzy Sets for Sample 1 | Fuzzy Sets for Sample 2 | Fuzzy Sets for Sample 3 |
|---|---|---|---|
| Water Content | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Iron (Fe) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Chromium (Cr) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Molybdenum (Mo) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Tin (Sn) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Lead (Pb) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Copper (Cu) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.75, Very Low), (0.25, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Aluminium (Al) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Silicon (Si) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Sodium (Na) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(0.5, Very Low), (0.5, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| Vanadium (V) | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} | {(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)} |
| **Aggregation Result** | **{(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}** | **{(0.9561, Very Low), (0.0439, Low), (0, Average), (0, High), (0, Very High)}** | **{(1, Very Low), (0, Low), (0, Average), (0, High), (0, Very High)}** |

*Source: Test case data*

In a similar way, and based on the information in Tables 4.20 and 4.21, the membership functions of the elements in the crane hydraulic pump oil samples are constructed as shown in Figures 1-4B4 to 11-4B4, Appendix 4B4. Trend analysis for the fuzzy set of crane hydraulic oil samples 1, 2 and 3 is conducted and the results shown in Table 4.22.

### 4.3.9 Evaluation of Family Analysis (Step four)

Evaluation of family analysis for the four main criteria (bearing, clutch, gearbox and hydraulic pump) is carried out first, by determining the standard deviations of the laboratory test results for each of the elements in the grease/oil samples from both port and starboard cranes. Secondly, by transforming the grease sample element test results from the two cranes' bearings and the oil sample element test results from the two cranes' clutches, gearboxes and hydraulic pumps to a linguistic variables with the associated belief degrees, using triangular membership functions of continuous fuzzy sets. This is illustrated in subsequent sections.

#### 4.3.9.1 Evaluation of family analysis for crane bearing

Table 4.23 shows the standard deviation of both the port and starboard ship deck crane obtained from their bearing grease samples laboratory test results taken for each element. To evaluate family analysis for each of the crane's bearing, each standard deviation of the element in the crane's bearing grease is transformed into linguistic variables with their associated belief degrees.

Based on expert opinions and by equal distribution of standard deviation, the following rules are demonstrated for all the test elements in Table 4.23:

1. If both cranes bearing grease sample laboratory test results have a standard deviation of 5 or lower, then it can be categorised as 100% Very Good.
2. If both cranes bearing grease sample laboratory test results have a standard deviation of 10 to 15, then it can be categorised as 100% Good.
3. If both cranes bearing grease sample laboratory test results have a standard deviation of 20 to 25, then it can be categorised as 100% Average.
4. If both cranes bearing grease sample laboratory test results has a standard deviation of 30 to 35, then it can be categorised as 100% Bad.
5. If both cranes bearing grease sample laboratory test results has a standard deviation of 40 and above, then it can be categorised as 100% Very Bad.

**Table 4.23.** Standard Deviation for Port and Starboard Cranes Bearing Grease Test Results

| PORT CRANE | | | | STARBOARD CRANE | | | | |
|---|---|---|---|---|---|---|---|---|
| **Test Elements** | Sample 3 | Sample 2 | Sample 1 | Sample 3 | Sample 2 | Sample 1 | Average Value | Standard Deviation |
| Iron (Fe) mg/kg | 43 | 20 | 27 | 69 | 46 | 20 | 37.5 | 19.07 |
| Chromium (Cr) mg | 0 | 0 | 5 | 0 | 0 | 5 | 1.667 | 2.582 |
| Molybdenum (Mo) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Tin (Sn) mg/kg | 15 | 0 | 0 | 7 | 10 | 1 | 5.5 | 6.221 |
| Lead (Pb) mg/kg | 45 | 5 | 14 | 39 | 14 | 23 | 23.33 | 15.65 |
| Copper (Cu) mg/k | 122 | 0 | 14 | 181 | 0 | 20 | 56.17 | 76.57 |
| Sodium (Na) mg/k | 84 | 59 | 0 | 108 | 56 | 0 | 51.17 | 43.88 |
| Magnesium (Mg) m | 0 | 24 | 0 | 0 | 32 | 0 | 9.333 | 14.68 |
| Nickel (Ni) mg/k | 5 | 1 | 72 | 8 | 3 | 3 | 15.33 | 27.86 |
| Aluminium (Al) m | 13 | 22 | 174 | 20 | 26 | 15 | 45 | 63.37 |
| Silicon (Si) mg | 8 | 51 | 30 | 4 | 66 | 30 | 31.5 | 24.01 |

*Source: Hypothetical data from a reputable oil test laboratory*

*Iron (Fe) element in bearing grease samples:*

Based on the stated rules, the membership functions of iron (Fe) element in crane bearing grease samples can be constructed as shown in Figure 4.11. Then, by viewing the standard deviation in iron (Fe) element as an independent criterion, the 19.07 deviations in the grease samples laboratory test results for the two cranes bearings indicate medium iron (Fe) contents in the grease samples. Thus, 19.07 deviation in iron (Fe) contents can be categorised as partially Average and partially Good.

Based on the information in Table 4.23, the standard deviation for iron (Fe) in the two cranes bearing grease samples test results is 19.07. Based on Figure 4.11 and Equation (2.6), the belief degrees are calculated as follows:

$H_{n+1}$ is the Average grade; $h_{n+1,i} = 20$

$H_n$ is the Good grade; $h_{n,i} = 15$

$h_i$ = 19, 15 < 19 < 20

$\beta_{n,i} = \frac{20-19}{20-15} = \frac{1}{5} = 0.2 =$ 20% with the Good grade.

$\beta_{n+1,i} = 1 - 0.2 = 0.8 =$ 80% with the Average grade.

Therefore, the standard deviation in iron (Fe) for the bearing grease samples set are assessed as:

**$\widetilde{Fe}$ = {(0, Very Good), (0.2, Good), (0.8, Average), (0, Bad), (0, Very Bad)}**

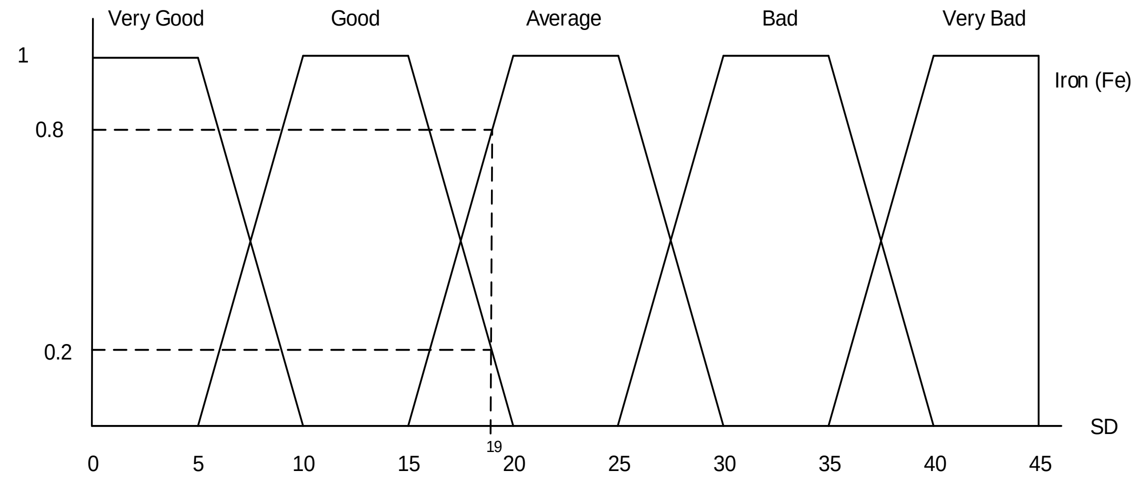


Figure 4.10: Membership Function of the Iron (Fe) Element – Family Analysis

Similarly, the membership functions for other elements in Table 4.23 for the crane bearing grease samples are constructed as shown in Figures 1-4C1 to 11-4C1, Appendix 4C1. The standard deviations for the oil samples set are assessed and their corresponding belief degrees are calculated and recorded in Table 4.24. With the help of the ER algorithm, the family analysis results for the crane bearing grease samples are recorded in Table 4.24.

**Table 4.24:** Fuzzy Sets for Crane Bearing Oil Samples – Family Analysis

| **Test Elements** | **Estimates** |
|---|---|
| Iron (Fe) | {(0, Very Good), (0.2, Good), (0.8, Average), (0, Bad), (0, Very Bad)} |
| Chromium (Cr) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Molybdenum (Mo) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Tin (Sn) | {(0.76, Very Good), (0.24, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Lead (Pb) | {(0, Very Good), (0.86, Good), (0.14, Average), (0, Bad), (0, Very Bad)} |
| Copper (Cu) | {(0, Very Good), (0, Good), (0, Average), (0, Bad), (1, Very Bad)} |
| Sodium (Na) | {(0, Very Good), (0, Good), (0, Average), (0, Bad), (1, Very Bad)} |
| Magnesium (Mg) | {(0, Very Good), (1, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Nickel (Ni) | {(0, Very Good), (0, good), (0.4, Average), (0.6, Bad), (0, Very Bad)} |
| Aluminium (Al) | {(0, Very Good), (0, Good), (0, Average), (0, Bad), (1, Very Bad)} |
| Silicon (Si) | {(0, Very Good), (0, Good), (1, Average), (0, Bad), (0, Very Bad)} |
| **$\widetilde{FA}$ for Crane Bearings** | **{(0.253, Very Good), (0.2076, Good), (0.2118, Average), (0.0503, Bad), (0.2773, Very Bad)}** |

*Source: Test case data*

### 4.3.9.2 Evaluation of family analysis for crane clutch

Table 4.25 shows the standard deviation of both the port and starboard ship deck crane obtained from the clutch oil samples laboratory test results taken for each element. By applying the same techniques described in Section 4.3.9.1, and based on the information in Table 4.25, the membership functions of the elements in the crane clutch oil samples are constructed as shown in Figures 1-4C2 to 10-4C2, Appendix 4C2. With the help of the ER algorithm, family analysis for the fuzzy set of crane clutch oil samples are conducted and the results recorded in Table 4.26.

**Table 4.25:** Standard Deviation for Port and Starboard Cranes Clutch Oil Test Results

| | PORT CRANE | | | STARBOARD CRANE | | | | |
|---|---|---|---|---|---|---|---|---|
| **Test Elements** | Sample 3 | Sample 2 | Sample 1 | Sample 3 | Sample 2 | Sample 1 | Average Value | Standard Deviation |
| Iron (Fe) | 6 | 8 | 8 | 11 | 11 | 10 | 9 | 2 |
| Chromium (Cr) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Molybdenum (Mo) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Tin (Sn) | 1 | 0 | 1 | 4 | 4 | 3 | 2.167 | 1.722 |
| Lead (Pb) | 1 | 1 | 2 | 1 | 1 | 0 | 1 | 0.632 |
| Copper (Cu) | 5 | 6 | 5 | 10 | 10 | 9 | 7.5 | 2.429 |
| Magnesium (Mg) | 13 | 13 | 10 | 19 | 20 | 17 | 15.33 | 3.933 |
| Aluminium (Al) | 1 | 0 | 0 | 2 | 2 | 0 | 0.833 | 0.983 |
| Silicon (Si) | 4 | 5 | 4 | 5 | 5 | 6 | 4.833 | 0.753 |
| Vanadium (V) | 9 | 10 | 8 | 15 | 17 | 14 | 12.17 | 3.656 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 4.26:** Fuzzy Sets for Crane Clutch Oil Samples – Family Analysis

| **Test Elements** | **Estimates** |
|---|---|
| Iron (Fe) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Chromium (Cr) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Molybdenum (Mo) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Tin (Sn) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Lead (Pb) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Copper (Cu) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Magnesium (Mg) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Aluminium (Al) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Silicon (Si) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Vanadium (V) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| **$\widetilde{FA}$ for Crane Clutches** | **{(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)}** |

*Source: Test case data*

#### 4.3.9.3 Evaluation of family analysis for crane gearbox

Table 4.27 shows the standard deviation of both the port and starboard ship deck crane obtained from their gearbox oil samples laboratory test results taken for each element. Applying the same techniques described Section 4.3.9.1, and based on the information in Tables 4.27, the membership functions of the elements in the crane gearbox oil samples are constructed as shown in Figures 1-4C3 to 14-4C3, Appendix 4C3. Family analysis for the fuzzy set of crane gearbox oil samples are conducted and the results recorded in Table 4.28.

#### 4.3.9.4 Evaluation of family analysis for crane hydraulic pump

Table 4.29 shows the standard deviation of both the port and starboard ship deck crane obtained from their hydraulic oil samples laboratory test results taken for each element. Applying the same techniques described in Section 4.3.9.1, and based on the information in Tables 4.29, the membership functions of the elements in the crane hydraulic pump oil samples are constructed as shown in Figures 1-4C4 to 14-4C4, Appendix 4C4. The family analysis for the fuzzy set of crane hydraulic pump oil samples are conducted and the results recorded in Table 4.30.

**Table 4.27:** Standard Deviation for Port and Starboard Cranes Gearbox Oil Test Results

| | PORT CRANE | | | STARBOARD CRANE | | | | |
|---|---|---|---|---|---|---|---|---|
| **Test Elements** | Sample 3 | Sample 2 | Sample 1 | Sample 3 | Sample 2 | Sample 1 | Average Value | Standard Deviation |
| Water Content %v | 0.1 | 0 | 0 | 0 | 0 | 0 | 0.017 | 0.041 |
| Total Acid No. (TAN) | 0.31 | 0.42 | 0.37 | 0.36 | 0.43 | 0.67 | 0.427 | 0.127 |
| Iron (Fe) mg/kg | 13 | 11 | 15 | 13 | 16 | 20 | 14.67 | 3.141 |
| Chromium (Cr) mg | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Molybdenum (Mo) | 187 | 259 | 513 | 253 | 488 | 598 | 383 | 170.2 |
| Tin (Sn) mg/kg | 3 | 0 | 22 | 1 | 0 | 0 | 4.333 | 8.733 |
| Lead (Pb) mg/kg | 0 | 0 | 0 | 0 | 0 | 4 | 0.667 | 1.633 |
| Copper (Cu) mg/k | 31 | 29 | 36 | 24 | 32 | 38 | 31.67 | 5.007 |
| Sodium (Na) mg/k | 0 | 3 | 0 | 0 | 3 | 4 | 1.667 | 1.862 |
| Magnesium (Mg) m | 1 | 0 | 1 | 1 | 0 | 1 | 0.667 | 0.516 |
| Boron (B) mg/kg | 3 | 0 | 0 | 0 | 0 | 0 | 0.5 | 1.225 |
| Aluminium (Al) m | 4 | 3 | 6 | 6 | 7 | 12 | 6.333 | 3.141 |
| Silicon (Si) mg/ | 4 | 4 | 9 | 9 | 11 | 15 | 8.667 | 4.227 |
| Vanadium (V) mg/ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 4.28:** Fuzzy Sets for Crane Gearbox Oil Samples – Family Analysis

| **Test Elements** | **Estimates** |
|---|---|
| Water Contents %v | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Total Acid Number (TAN) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Iron (Fe) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Chromium (Cr) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Molybdenum (Mo) | {(0, Very Good), (0, Good), (0, Average), (0, Bad), (1, Very Bad)} |
| Tin (Sn) | {(0.26, Very Good), (0.74, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Lead (Pb) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Copper (Cu) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Sodium (Na) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Magnesium (Mg) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Boron (B) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Aluminium (Al) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Silicon (Si) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Vanadium (V) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| **$\widetilde{FA}$ for Crane Gearboxes** | **{(0.9172, Very Good), (0.0352, Good), (0, Average), (0, Bad), (0.0476, Very Bad)}** |

*Source: Test case data*

**Table 4.29:** Standard Deviation for Port and Starboard Cranes Hydraulic Pump Test Results

| | PORT CRANE | | | STARBOARD CRANE | | | | |
|---|---|---|---|---|---|---|---|---|
| **Test Elements** | Sample 3 | Sample 2 | Sample 1 | Sample 3 | Sample 2 | Sample 1 | Average Value | Standard Deviation |
| Water Content %v | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Total Acid No. (TAN) | 0.55 | 0.5 | 0.5 | 0.48 | 0.34 | 0.42 | 0.465 | 0.074 |
| Iron (Fe) | 0 | 0 | 1 | 0 | 0 | 0 | 0.167 | 0.408 |
| Chromium (Cr) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Molybdenum (Mo) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Tin (Sn) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lead (Pb) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Copper (Cu) | 0 | 9 | 7 | 0 | 6 | 3 | 4.167 | 3.764 |
| Sodium (Na) | 0 | 9 | 0 | 0 | 6 | 0 | 2.5 | 3.987 |
| Magnesium (Mg) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Boron (B) | 0 | 1 | 0 | 0 | 1 | 0 | 0.333 | 0.516 |
| Aluminium (Al) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Silicon (Si) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Vanadium (V) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 4.30:** Estimates for Crane Hydraulic Pump Oil Samples – Family Analysis

| Test Elements | Estimates |
|---|---|
| Water Contents %v | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Total Acid Number (TAN) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Iron (Fe) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Chromium (Cr) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Molybdenum (Mo) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Tin (Sn) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Lead (Pb) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Copper (Cu) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Sodium (Na) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Magnesium (Mg) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Boron (B) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Aluminium (Al) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Silicon (Si) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| Vanadium (V) | {(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)} |
| **$\widetilde{FA}$ for Crane Hydraulic Pump** | **{(1, Very Good), (0, Good), (0, Average), (0, Bad), (0, Very Bad)}** |

*Source: Test case data*

### 4.3.10 Evaluation of Environmental Analysis (Step five)

The ship crane operating environmental information is not readily available making it difficult to know the exact environmental conditions during crane operations. With this lack of environmental data, the environmental conditions for the crane is assessed in different conditions of operation, with weights distributed evenly, when the environment is 100% very good, 100% good, 100% average, 100% bad, and 100% very bad.

A ship crane operating in a 100% very good environment is assessed as:

$\widetilde{E_1}$ = {(0, Very Bad), (0, Bad), (0, Average), (0, Good), (1, Very Good)}

A ship crane operating in a 100% good environment is assessed as:

$\widetilde{E_2}$ = {(0, Very Bad), (0, Bad), (0, Average), (1, Good), (0, Very Good)}

A ship crane operating in a 100% average environment is assessed as:

$\widetilde{E_3}$ = {(0, Very Bad), (0, Bad), (1, Average), (0, Good), (0, Very Good)}

A ship crane operating in a 100% bad environment is assessed as:

$\widetilde{E_4}$ = {(0, Very Bad), (1, Bad), (0, Average), (0, Good), (0, Very Good)}

A ship crane operating in a 100% very bad environment is assessed as:

$\widetilde{E_5}$ = {(1, Very Bad), (0, Bad), (0, Average), (0, Good), (0, Very Good)}

### 4.3.11 Evaluation of Human Reliability Analysis (Step six)

Based on the research carried out by Riahi *et al.* (2012), the human reliability belief degrees for the crane bearing, clutch, gearbox and the hydraulic pump are assessed as:

**$\widetilde{HRA}$ = {(0.1649, High), (0.1958, Fairly High), (0.4355, Medium), (0.2038, Fairly Low), (0, Low)}**

4.3.12 Evaluation of Design Analysis (Step seven)

In the test case, the machine components specified by the manufacturers as Good are given an attribute of 1, while the machine components specified as Bad are given an attributed of 0. Considering the four components (main criteria) of the crane, according to the crane manufacturer, these components are said to be in good condition. Thus, based on the manufacturer's recommendation, the design analysis belief degrees for each crane bearing, clutch, gearbox, and the hydraulic pump, can be assessed as:

$\widetilde{DA}$ = {(0, Very Bad), (0, Bad), (0, Average), (1, Good), (0, Very Good)}

4.3.13 Aggregation Operations on Criteria Results using ER (Step eight)

Aggregation operations on the sub-criteria and the main criteria are carried out using the ER algorithm (Equations (2.13) to (2.22)), and the weights (Table 4.9) obtained with the help of AHP, as follows:

4.3.13.1 Aggregation of sub-criteria

The sub-criteria (TA, FA, EA, HRA and DA) for the three oil samples (1, 2 and 3) are aggregated, as shown in Tables 1-4D to 12-4D (Appendix 4D), and the results are presented in Tables 4.31, 4.32 and 4.33.

**Table 4.31:** Aggregation Results of Sub-Criteria for Sample 1

| | |
|---|---|
| Bearing ($B_1$) | {(0.2251, Very Bad), (0.0658, Bad), (0.0978, Average), (0.1996, Good), (0.4117, Very Good)} |
| Clutch ($C_1$) | {(0.0121, Very Bad), (0.0129, Bad), (0.0191, Average), (0.1552, Good), (0.8006, Very Good)} |
| Gearbox ($G_1$) | {(0.1602, Very Bad), (0.0403, Bad), (0.0205, Average), (0.1615, Good), (0.6175, Very Good)} |
| Hydraulic Pump ($H_1$) | {(0.0124, Very Bad), (0.0130, Bad), (0.0182, Average), (0.0132, Good), (0.9432, Very Good)} |

*Source: Test case data*

**Table 4.32:** Aggregation Results of Sub-Criteria for Sample 2

| | |
|---|---|
| Bearing ($B_2$) | {(0.0460, Very Bad), (0.0275, Bad), (0.0490, Average), (0.1395, Good), (0.7380, Very Good)} |
| Clutch ($C_2$) | {(0.0094, Very Bad), (0.0100, Bad), (0.0148, Average), (0.0254, Good), (0.9404, Very Good)} |
| Gearbox ($G_2$) | {(0.0412, Very Bad), (0.0366, Bad), (0.0198, Average), (0.0478, Good), (0.8545, Very Good)} |
| Hydraulic Pump ($H_2$) | {(0.0127, Very Bad), (0.0134, Bad), (0.0186, Average), (0.0283, Good), (0.9269, Very Good)} |

*Source: Test case data*

**Table 4.33:** Aggregation Results of Sub-Criteria for Sample 3

| | |
|---|---|
| Bearing ($B_3$) | {(0.1754, Very Bad), (0.0296, Bad), (0.0820, Average), (0.0835, Good), (0.6294, Very Good)} |
| Clutch ($C_3$) | {(0.0092, Very Bad), (0.0098, Bad), (0.0146, Average), (0.0162, Good), (0.9501, Very Good)} |
| Gearbox ($G_3$) | {(0.0962, Very Bad), (0.0341, Bad), (0.0502, Average), (0.0515, Good), (0.7680, Very Good)} |
| Hydraulic Pump ($H_3$) | {(0.0124, Very Bad), (0.0130, Bad), (0.0182, Average), (0.0132, Good), (0.9432, Very Good)} |

*Source: Test case data*

4.3.13.2 Aggregation of the main criteria

Based on the expert judgements, the main criteria are equally important. Therefore, the weights for the main criteria are evenly distributed among them. Samples 1, 2 and 3 fuzzy output sets – ($B_1$, $C_1$, $G_1$, $H_1$), ($B_2$, $C_2$, $G_2$, $H_2$) and ($B_3$, $C_3$, $G_3$, $H_3$) respectively – are aggregated with the help of the ER algorithm and the results are presented in Tables 4.34, 4.35 and 4.36.

**Table 4.34:** Aggregation of Main Criteria from Fuzzy Sets Output of Sample 1

| Main Criteria | Fuzzy Set | Utility Value |
|---|---|---|
| Bearing ($B_1$) | {(0.2251, Very Bad), (0.0658, Bad), (0.0978, Average), (0.1996, Good), (0.4117, Very Good)} | 0.6268 |
| Clutch ($C_1$) | {(0.0121, Very Bad), (0.0129, Bad), (0.0191, Average), (0.1552, Good), (0.8006, Very Good)} | 0.9299 |
| Gearbox ($G_1$) | {(0.1602, Very Bad), (0.0403, Bad), (0.0205, Average), (0.1615, Good), (0.6175, Very Good)} | 0.7590 |
| Hyd. Pump ($H_1$) | {(0.0124, Very Bad), (0.0130, Bad), (0.0182, Average), (0.0132, Good), (0.9432, Very Good)} | 0.9655 |
| **Aggregation result ($S_1$)** | **{(0.0829, Very Bad), (0.0261, Bad), (0.0308, Average), (0.1095, Good), (0.7507, Very Good)}** | **0.8548** |

*Source: Test case data*

**Table 4.35:** Aggregation of Main Criteria from Fuzzy Sets Output of Sample 2

| Main Criteria | Fuzzy Set | Utility Value |
|---|---|---|
| Bearing ($B_2$) | {(0.0460, Very Bad), (0.0275, Bad), (0.0490, Average), (0.1395, Good), (0.7380, Very Good)} | 0.8740 |
| Clutch ($C_2$) | {(0.0094, Very Bad), (0.0100, Bad), (0.0148, Average), (0.0254, Good), (0.9404, Very Good)} | 0.9694 |
| Gearbox ($G_2$) | {(0.0412, Very Bad), (0.0366, Bad), (0.0198, Average), (0.0478, Good), (0.8545, Very Good)} | 0.9095 |
| Hyd. Pump ($H_2$) | {(0.0127, Very Bad), (0.0134, Bad), (0.0186, Average), (0.0283, Good), (0.9269, Very Good)} | 0.9609 |
| **Aggregation result ($S_2$)** | **{(0.0190, Very Bad), (0.0152, Bad), (0.0178, Average), (0.0425, Good), (0.9054, Very Good)}** | **0.9500** |

*Source: Test case data*

**Table 4.36:** Aggregation of Main Criteria from Fuzzy Sets Output of Sample 3

| Main Criteria | Fuzzy Set | Utility Value |
|---|---|---|
| Bearing ($B_3$) | {(0.1754, Very Bad), (0.0296, Bad), (0.0820, Average), (0.0835, Good), (0.6294, Very Good)} | 0.7405 |
| Clutch ($C_3$) | {(0.0092, Very Bad), (0.0098, Bad), (0.0146, Average), (0.0162, Good), (0.9501, Very Good)} | 0.9721 |
| Gearbox ($G_3$) | {(0.0962, Very Bad), (0.0341, Bad), (0.0502, Average), (0.0515, Good), (0.7680, Very Good)} | 0.8403 |
| Hyd. Pump ($H_3$) | {(0.0124, Very Bad), (0.0130, Bad), (0.0182, Average), (0.0132, Good), (0.9432, Very Good)} | 0.9655 |
| **Aggregation result ($S_3$)** | **{(0.0536, Very Bad), (0.0156, Bad), (0.0299, Average), (0.0298, Good), (0.8711, Very Good)}** | **0.9123** |

*Source: Test case data*

### 4.3.14 Obtaining a Crisp Number for the Goal (Step Nine)

Based on Tables 4.34, 4.35, and 4.36, the sample 1 ($S_1$), sample 2 ($S_2$), and sample 3 ($S_3$) fuzzy output sets for the crane's condition (i.e. Goal) are obtained as:

$\widetilde{S_1}$ = {(0.0829, Very Bad), (0.0261, Bad), (0.0308, Average), (0.1095, Good), (0.7507, Very Good)}

$\widetilde{S_2}$ = {(0.0190, Very Bad), (0.0152, Bad), (0.0178, Average), (0.0425, Good), (0.9054, Very Good)}

$\widetilde{S_3}$ = {(0.0536, Very Bad), (0.0156, Bad), (0.0299, Average), (0.0298, Good), (0.8711, Very Good)

To obtain a single crisp value for each of the three samples, the utility value associated with each linguistic term is calculated using Equations (4.2) to (4.4), as shown in Table 4.37. Considering the fact that the fuzzy output sets for the crane (Goal) are characterised by five linguistic terms, the highest preference is given to the Very Good linguistic term, while the lowest preference is given to the Very Bad linguistic term. Therefore, the ranking value is apportioned from five (i.e. highest preference) to one (i.e. lowest preference). The crane's assessments, as shown in Table 4.37, are complete. The utility values of the crane based on sample 1 ($S_1$), sample 2 ($S_2$), and sample 3 ($S_3$), as shown in Table 4.37, are calculated to be:

**$S_1$ = 0.8548**, **$S_2$ = 0.9500**, **$S_3$ = 0.9123**

From the utility values obtained, it can be noted that sample 2 ($S_2$) scores the highest utility value of 0.950. From these results it can be deduced that the crane's condition was not very good when oil sample 1 was being taken from the components and sent for testing, then the condition was improved when oil sample 2 was taken, but started deteriorating when oil sample 3 was taken. However, it can be argued that either the oil topping or sampling intervals can influence the results.

**Table 4.37:** Utility Value

| $H_n$ | Very Good | Good | Average | Bad | Very Bad |
|---|---|---|---|---|---|
| $V_n$ | 5 | 4 | 3 | 2 | 1 |
| $U(H_n)$ | $\frac{5-1}{5-1}=1$ | $\frac{4-1}{5-1}=0.75$ | $\frac{3-1}{5-1}=0.5$ | $\frac{2-1}{5-1}=0.25$ | $\frac{1-1}{5-1}=0$ |
| | | | | | |
| $\beta_n(S1)$ | 0.7507 | 0.1095 | 0.0308 | 0.0261 | 0.0829 |
| $\sum_{n=1}^{5}\beta_n$ | 0.7507 + 0.1095 + 0.0308 + 0.0261 + 0.0829 = 1 (complete) | | | | |
| $\beta_n U(H_n)$ | 0.7507 | 0.082125 | 0.0154 | 0.006525 | 0 |
| $S_1$ Condition values of the crane = $\sum_{n=1}^{5}\beta_n\,U(H_n)=0.85475 \approx 0.8548$ | | | | | |
| $\beta_n(S2)$ | 0.9054 | 0.0425 | 0.0178 | 0.0152 | 0.0190 |
| $\sum_{n=1}^{5}\beta_n$ | 0.9054 + 0.0425 + 0.0178 + 0.0152 + 0.0190 = 1 (complete) | | | | |
| $\beta_n U(H_n)$ | 0.9054 | 0.031875 | 0.0089 | 0.0038 | 0 |
| $S_2$ Condition values of the crane = $\sum_{n=1}^{5}\beta_n\,U(H_n)=0.949975 \approx 0.9500$ | | | | | |
| $\beta_n(S3)$ | 0.8711 | 0.0298 | 0.0299 | 0.0156 | 0.0536 |
| $\sum_{n=1}^{5}\beta_n$ | 0.8711 + 0.0298 + 0.0299 + 0.0156 + 0.0536 = 1 (complete) | | | | |
| $\beta_n U(H_n)$ | 0.8711 | 0.02235 | 0.01495 | 0.0039 | 0 |
| $S_3$ Condition values of the crane = $\sum_{n=1}^{5}\beta_n\,U(H_n)=0.9123$ | | | | | |

*Source: Test case data*

Similarly, to assess the condition of the main criteria, the utility values for each main criterion in samples 1, 2, and 3 are calculated and the results shown in Tables 4.34, 4.35, and 4.36 respectively.

4.3.15 Sensitivity Analysis (Final step)

To test the certainty of the delivery of the analysis results, the three axioms mentioned in Section 4.2.10 are used in the sample 2 input data in Tables 5-4D to 8-4D (Appendix 4D). The degrees of belief associated with the highest preference linguistic values of all the combined sub-criteria are decreased by 0.2, while simultaneously increasing the degrees of belief associated with the lowest preference linguistic values of each of the combined sub-criteria, as shown in Appendix 4E (Tables 1-4E to 4-4E). The aggregation results obtained are shown in Table 4.38. All the results obtained remain in harmony with axioms 1 and 2. Also, by using a similar technique to that described in Section 4.3.14, the crane's utility value from a 0.2 decrement of sample 2 input data is evaluated to be 0.7774, as shown in Table 4.38.

To examine the alignment of the model with axiom 3, each original fuzzy set results for sample 2 in Table 4.32 and the 0.2 decrement fuzzy set results for sample 2 in Table 4.38 are varied and aggregated using the ER algorithm, as shown in Tables 1-4F to 4-4F of Appendix 4F. The results obtained are shown in Table 4.39. The comparative utility values (ship crane reliability) for the crane bearing ($B_2$), clutch ($C_2$), gearbox ($G_2$), and hydraulic pump ($H_2$) obtained are also listed in Table 4.39 and shown in Figure 4.12. The lowest utility value of the ship crane is evaluated as 0.909. In view of the fact that 0.7774 (value of aggregation result in Table 4.38) is smaller than 0.909, this means the result is aligned with Axiom 3.

From Figure 4.12, it is obvious that the ship crane is more sensitive to the crane bearing ($B_2$) and gearbox ($G_2$) than to the other main-criteria. Therefore, the ranking orders in Figure 4.12 are consistent with those given by Lloyd's Register (2011), Aldridge (2012) and Konecranes (2012).

**Table 4.38:** Aggregation Results for Sample 2 Due to Decrement by 0.2

| Main Criteria | Fuzzy Set | Utility Value |
|---|---|---|
| Bearing ($B_2$) | {(0.2483, Very Bad), (0.0301, Bad), (0.0536, Average), (0.1525, Good), (0.5155, Very Good)} | 0.6642 |
| Clutch ($C_2$) | {(0.1797, Very Bad), (0.0115, Bad), (0.0170, Average), (0.0291, Good), (0.7627, Very Good)} | 0.7959 |
| Gearbox ($G_2$) | {(0.2330, Very Bad), (0.0410, Bad), (0.0221, Average), (0.0535, Good), (0.6503, Very Good)} | 0.7118 |
| Hydraulic Pump ($H_2$) | {(0.1863, Very Bad), (0.0153, Bad), (0.0213, Average), (0.0324, Good), (0.7447, Very Good)} | 0.7835 |
| **Aggregation Result** | **{(0.1835, Very Bad), (0.0193, Bad), (0.0225, Average), (0.0536, Good), (0.7211, Very Good)}** | **0.7774** |

*Source: Test case data*

**Table 4.39:** Aggregation Results for the Variation of each 0.2 Decrement Values with the Original Fuzzy Sets in the Main Criteria

| Main Criteria | Sample 2 Fuzzy Set | Utility Value |
|---|---|---|
| Bearing ($B_2$) | {(0.0572, Very Bad), (0.0164, Bad), (0.0195, Average), (0.0470, Good), (0.8599, Very Good)} | 0.909 |
| Clutch ($C_2$) | {(0.0510, Very Bad), (0.0160, Bad), (0.0188, Average), (0.0446, Good), (0.8695, Very Good)} | 0.916 |
| Gearbox ($G_2$) | {(0.0550, Very Bad), (0.0166, Bad), (0.0190, Average), (0.0453, Good), (0.8641, Very Good)} | 0.912 |
| Hydraulic Pump ($H_2$) | {(0.0517, Very Bad), (0.0161, Bad), (0.0189, Average), (0.0448, Good), (0.8686, Very Good)} | 0.916 |

*Source: Test case data*

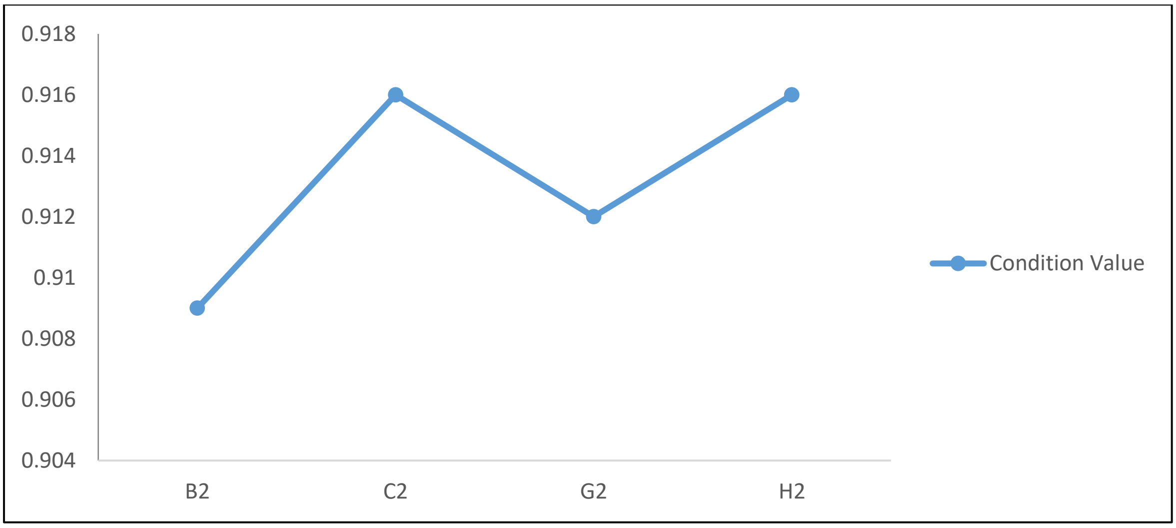


Figure 4.11: Sensitivity of the Model Output to the Variation of the Alteration with Original in each Main Criterion

## 4.4 Discussions

This chapter outlines a novel methodology for evaluating a ship's crane performance by means of its conditional reliability. The methodology for evaluating a ship's crane reliability and the procedure for applying it in a real life scenario has been illustrated in the case study in Section 4.3. This model is one of the first to concede that a ship's crane reliability value is not fixed and it may change due to certain factors, such as the trend analysis (i.e. pattern of behaviour developed over a period of time), family analysis (i.e. typical identical pattern of behaviour), environmental analysis (i.e. changes in the sea state), human reliability analysis (i.e. operator's well-being), as well as design analysis (i.e. crane's physical behaviour as stated by the manufacturer).

For example, if the grade of design analysis in a ship's crane bearing is very bad, and the grade of the environment (sea condition) is very rough, then owing to the roughness of the sea and instability of the ship, the engineer on-board would not be able to carry out the scheduled maintenance work on the crane's bearing. Thus, the crane grade will decrease from a good grade to an average grade. As a result, the reliability of the crane will alter. The oil sample 2 reliability value for the ship's crane bearing when the environmental condition was good ($E_2$ value in Table 5-4C, Appendix 4C) is 4.6% lower than that of the same crane's bearing with a very good grade of design when operating in a very good environmental condition ($E_1$ value in Table 5-4C, Appendix 4C). Therefore, during the conceptual stage of the ship's crane bearing design, the manufacturer should take into consideration uncertain environmental conditions throughout the life cycle of the crane bearing.

The gearbox is another component that can significantly influence a ship's crane reliability. Based on the analysis, it can be deduced that if the grade in a ship's crane gearbox is very high (0.9095 in Table 4.35), then the crane's reliability value is about 11% more than that of the same crane with a very low grade (0.7590 in Table 4.34). Furthermore, according to Figure 4.12, $B_{2,}$ and $G_{2,}$ are recorded low condition values for crane bearing and gearbox alterations respectively when compared to other crane components.

A survey conducted by Lloyd's Register (2011) indicates that several slew bearings failures have occurred in cranes in recent years, with catastrophic results. Moreover, based on an incident report by Aldridge (2012) and case study by Konecranes (2012), gearbox malfunction is very common in ship cranes, while the crane reliability survey (CRS) shows that gearbox failures can result in catastrophic crane failure. Thus, the results of these analyses confirmed their findings, and gives emphasis to the importance of design, inspections, and condition monitoring in ship's crane components.

The evaluation of a ship's crane performance can be used to develop a preventive measure against incidents. This can be achieved by correctly measuring the crane's performance and regularly taking oil samples from the crane's components and analysing it as scheduled. The grade of a ship's crane performance is significant in identifying and taking preventive measures against incidents at sea, as well as in ports, and for ensuring the appropriate performance of operations on-board.

A ship's crane design is highly dependent on the crane's manufacturer and the ship owner's requirements, whereas, the ship's crane trend analysis, family analysis, and human reliability analysis are highly dependent on the ship owner's strategies. Unfortunately, not much can be done with regards to the environmental analysis, as this is a natural phenomenon that is not dependent on either the ship owner or the ship crane manufacturer.

However, with proper ship crane design and the implementation of correct condition monitoring strategies, the environmental impacts can be significantly reduced and well managed, therefore leading to a reduction in the frequency of ship crane incidents. Furthermore, a well-structured maintenance regime, in accordance with the manufacturer’s recommendations, can reduce the chances of unexpected defects occurring and can ultimately improve the reliability and operational life of the crane.

## 4.5 Conclusion

This chapter has proposed a *FER-SAM* to monitor the ship’s crane risk of failure in a systematic fashion. The usefulness of the *FER-SAM* is demonstrated for condition-based decision-making. The approach outlined how a subjective condition-based decision making process can be achieved during situations of high uncertainties in ship’s crane operations. The subjective condition monitoring of the investigated system parameters was first carried out using an AHP approach, then assessment grades were mapped into a common utility space before synthesizing for robust decision-making. This generic approach has highlighted a unique feature associated with the performance and unification of input and output data.

The ER approach employed provides a procedure for aggregation which can preserve the original features of multiple attributes under high and imprecise situations. The inclusion of trend analysis, family analysis, environmental analysis, human reliability, and design analysis to the ship's crane condition monitoring approach (CMA) will help to ensure that findings are incorporated within the maintenance management process for future reference. If each of the analyses is applied to each wear metal for each crane component tested in a programme, the data evaluation process will become too clumsy. Therefore, realistically, the ideal analysis programme would be a combination of the five analysis techniques discussed in this research work.

This approach also provides a rational, reliable and transparent method for decision-making analysis with a group of experts under situations of high uncertainties. It can therefore be reasonably expected that the application of this approach will facilitate the development of a robust and enhanced marine and offshore environment for machinery systems operations. As revealed in the final result, the developed *FER-SAM* does provide some levels of confidence in monitoring the condition of ship’s crane components; however, it cannot deal with the dependencies of the criteria. It is therefore essential to develop an integrated risk assessment using Fuzzy Rule Base Method that will account for this shortfall in a systematic manner, and this is provided in the next chapter.

# Chapter 5

# An Integrated Risk Assessment for Maintenance Prediction of Oil Wetted Gearbox and Bearing in Marine and Offshore Industries Using a Fuzzy Rule Base Method


## Summary

This chapter presents an integrated risk assessment methodology for maintenance prediction of oil wetted gearbox and bearing in marine and offshore machinery with emphasis on ship cranes. Predictive maintenance uses important parameters measured in the equipment to “feel” when breakdown is eminent. This type of maintenance intends to make interventions on machinery before harmful events may occur (Bastos *et al.*, 2012).

In Chapter 4, the analysis result indicated that both bearing and gearbox are the most sensitive components of the ship crane. The aim of this chapter is to assess the risk levels of these components (bearing and gearbox) using fuzzy rule based judgement for common elements and their sources, which will provide the ship crane operators with a means to predict possible impending failure without having to dismantle the crane. Furthermore, to monitor the rate of wear in gearbox and bearing of a ship crane, the ship crane reliability (SCR), and a trend to provide an operational baseline of data that will help the engineers to detect abnormal wear rates as they develop, are established.

Within the scope of this research, a risk assessment model will be developed that will be capable of determining the risk levels of a crane’s components and recommending solutions using all the diagnostic capability obtainable for effective condition monitoring of the gearbox and bearing in ship cranes.


## 5.1 Introduction

In today’s revolutionary computer and information age, oil sampling analysis has developed into a mandatory tool. It has not only proven to be an effective condition monitoring tool for equipment failure, but is also a crucial element in a marine crane’s condition monitoring. As a predictive maintenance tool, oil analysis can be used to uncover, isolate, and offer solutions for abnormal lubricant and machine conditions. If these abnormalities are left unchecked, they could have detrimental consequences, including health and safety risks.

Oil analysis is performed during routine preventive maintenance to provide meaningful and accurate information on lubricant and machine condition. By tracking oil analysis sample results over the life of a particular machine, trends can be established that could help eliminate costly repairs.

In addition to monitoring oil contamination and wear metals, modern usage of oil analysis includes the analysis of the additives in oils to determine if an extended drain interval may be used. Maintenance costs can be reduced using oil analysis to determine the remaining useful life of additives in the oil. By comparing the oil analysis results of fresh and used oil, a tribologist can determine when an oil must be replaced. Careful analysis might even allow the oil to be "sweetened" to its original additive levels by either adding fresh oil or replenishing additives that were depleted.

The information contained in this research is particularly useful for the effective condition monitoring of ship crane gearbox and bearing. This risk assessment tool can also be used as an information technology application to monitor the performance of lubricant products, as well as a tool that specifies what the problem/remedy is in the event of failure of a piece of equipment/component.

## 5.2. Used Oil Sampling Analysis of Marine Crane Bearing and Gearbox

Oil sampling analysis is known to be an effective condition-monitoring tool for marine crane bearing and gearbox diagnosis. This involves a representative sample being taken, which ensures that there is as much information per millimetre of oil as possible. This information relates to such criteria as cleanliness and dryness of the oil, depletion of additives, and the presence of wear particles being generated by the crane. The second goal is to minimize data disturbance. The sample should be extracted so that the concentration of information is uniform, consistent, and representative. The lubricant sample is then assessed by a suitable analytical method to identify signs of increased wear and evidence of unwanted contaminants or lubricant degradation. It is important to make sure that the sample does not become contaminated during the sampling process. This can distort and disturb the data, making it difficult to distinguish what was originally in the oil, from what came into the oil during the sampling process (Fitch, 2004).

## 5.3 Methodology

Investing in maintenance prediction in the operations of marine machinery system requires networks of robust decision making tailored towards improving the capability of the system to exhibit required performance. A major modelling assumption in this chapter is that, some overlaps in the description of all risk attributes can be observed, however, the main issue or content are largely independent which allows the use of rule based judgement for their aggregation and synthesis in a systematic method. This study employs a fuzzy set theory (*FST*) and a fuzzy rule based sensitivity analysis method (*FRB-SAM*), to model the risks impacting the smooth operation of the ship cranes' components.

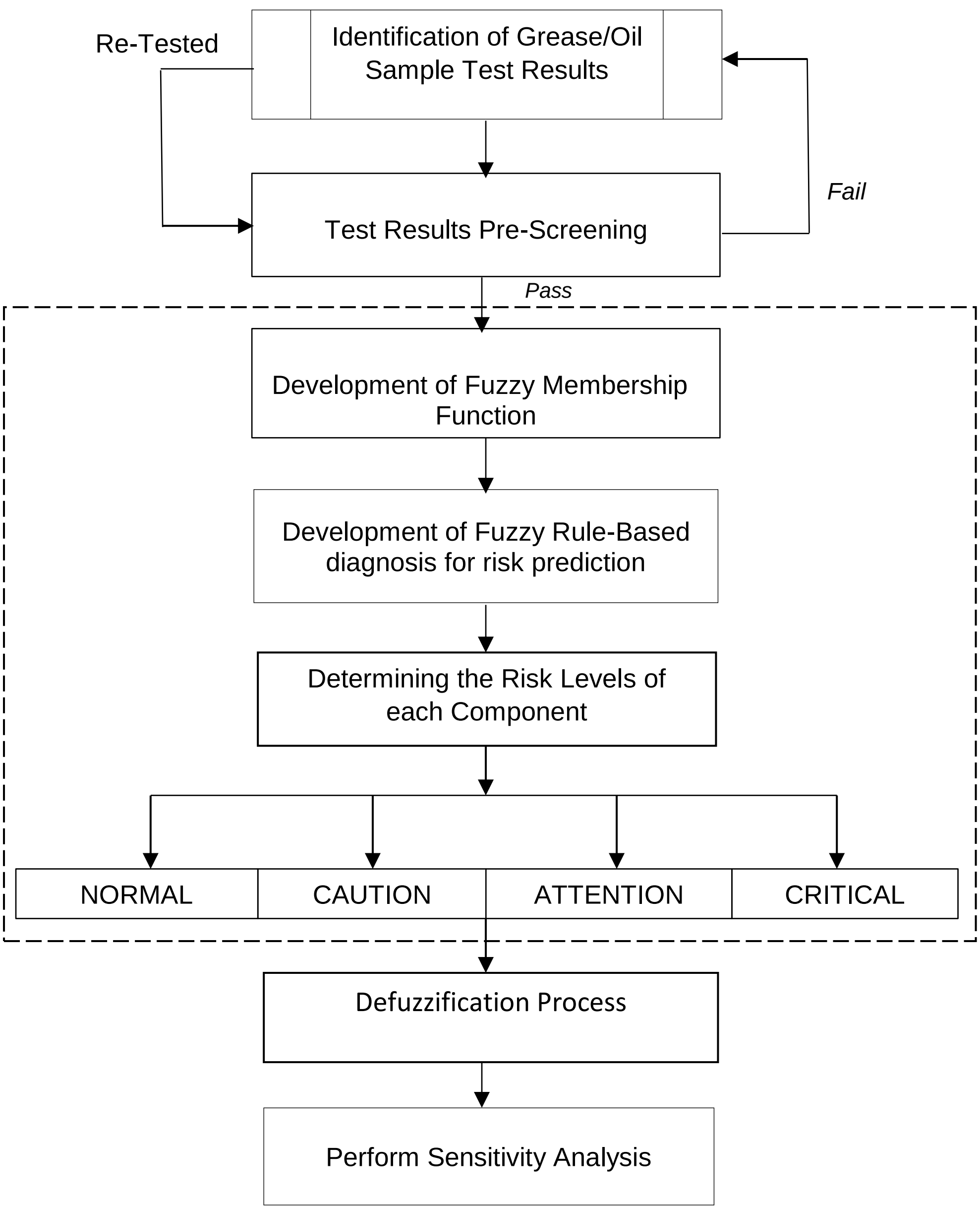


Figure 5.1: Diagnostic Flow Chart

The first step of the proposed framework is to identify the critical elements in an oil sample test results for the crane's bearing and the gearbox. The second step is to pre-screen the oil sample test results to identify inconsistency or out of range results. Developing fuzzy membership functions for the test elements of each crane's component that passes the pre-screening process follows this. The fourth step is to develop a FRB diagnosis for risk prediction of the crane's bearing and the gearbox. Lastly, a set of fuzzy conclusions is achieved using the "min-max" method.

Since the study incorporates FST into a FRB method, a set of linguistic priority terms along with the membership functions describing the relationship between elements in each hierarchy of the RB is adopted. Thus, the minimum value comparisons between the elements in each hierarchy using FST are established.

The proposed model in a stepwise regression is presented in the following sections and the framework of this methodology for evaluating the diagnostic process of the used oil sample test results for the crane bearing and gearbox is shown in Figure 5.1.

### 5.3.1 Identification of Grease/Oil Sample Test Results (Step one)

Under this process, critical elements in the used grease/oil laboratory analysis reports given in Chapter 4 are identified for both port and starboard deck crane slewing bearing/gearbox for the pre-screening process.

### 5.3.2 Pre-Screening of the Test Results (Step two)

The pre-screening process is used to identify inconsistency in the test results, out of range test results, or mistyping during test result entry as a result of human error. The process considers only numeric test results. At pre-screening, the sample test results are initially screened against a specific range (min – max values). The min and max values for an individual test can differ based on the laboratories and lubricant manufacturers. If the test element(s) in a sample fail pre-screening, the sample is sent back for retest. Pre-screening on a sample will then happen again when the re-tested results are entered (i.e. if sample is sent for retesting, it is considered again for the pre-screening until it passes the pre-screening process).

The following steps are part of the pre-screening process:

1. The pre-screening process fetches all the tests conducted for a sample, the test results, and their min/max values.
2. The sample test results are compared against the predefined min/max values.
3. A test fails pre-screening if the results are outside the min and max values. Failed test samples are sent for retest. During retest, the out of range values are normally corrected.
4. Retested samples are then sent through the pre-screening process.

*Rules for pre-screening process:*

IF (Test Result ≥ Lower Action) & (Test Result ≤ Upper Action)

THEN, *Pre-Screening Passed*

ELSE, *Pre-screening Failed*

*Explanation of the Rule:*
Each test result is checked to see whether it is within the min and max limits (i.e. Lower Action and Upper Action) set for that test; if it falls within that range, the test result passes *pre-screening*; otherwise, the sample fails *pre-screening*.

### 5.3.3 Development of Fuzzy Membership Function (Step three)

According to Wang (1997), fuzzy membership functions can be used to define the fuzzy input subset from an input variable. The membership functions considered in this study are based on the criteria for oil sample elements and are generated using triangular shapes to reduce computational times, unlike trapezoidal shapes which takes a longer time. A fuzzy membership function is developed for each of the identified critical elements based on their corresponding limits provided. These limits are obtained from a reputable oil company. The membership function for each linguistic priority term is evaluated within its limits on an arbitrary scale from 0 to 1. The fuzzy membership function has already been discussed extensively in Chapters 2 and 4 of this thesis.

### 5.3.4 Development of Fuzzy Rule-Based Diagnosis for Risk Prediction (Step four)

In this section, a fuzzy rule-based diagnosis is produced for predicting the condition of crane bearing and gearbox, utilising the laboratory oil sample test results as the input data. The linguistic terms used in developing the membership functions described in Section 5.3.3 are utilized to reflect the priority level of alertness.

### 5.3.5 Determining the Risk Levels of each Component (Step five)

The priority level (PL) of a specific scenario will be decided based on the fuzzy rule base developed in Section 5.3.4. Using a ‘min-max’ approach, the set of fuzzy conclusions of the scenario will be obtained in terms of membership function values associated with linguistic priority terms. In order to activate the developed rule base, firing rules will be used to obtain the output grade (i.e. normal, caution, attention, or critical) based on the results obtained from the *min-max* method. When applying the ‘min-max’ approach, the following steps are taken:

- Identify the possible combinations of the test elements in which the membership values associated with the corresponding linguistic priority terms are not zero. The outputs of such combinations can be obtained from the fuzzy rule base developed. Obtaining the output of the test elements combinations from the fuzzy rule base is also known as *firing rules.*
- Determine the minimum value of each combination by comparing the values obtained from each element and the value of the belief degree established in the priority level (PL).
- Determine the highest minimum values obtained from step 2 with respect to each linguistic priority term.

From the above, each maximum value and its associated linguistic priority term is a fuzzy conclusion. Each set of fuzzy conclusions of each scenario will be defuzzified using the method proposed in Section 5.3.6. If there is only one rule that can be applied to the scenario in question, then the minimum value of the membership function and the linguistic priority term associated will be the set of fuzzy conclusions.

### 5.3.6 Defuzzification Process (Step six)

The defuzzification process is used to create a single crisp ranking from the fuzzy conclusion set (i.e. the priority level of scenarios to express the machinery condition). According to Runkler and Glesner (1993), several defuzzification algorithms have been developed and used in creating a single crisp ranking. The one selected for use in this chapter is the weighted arithmetic mean (WAM) of non-empty set of data. This algorithm averages the points of maximum possibility of each priority level of scenarios, weighted by their degree of truth at which the membership functions reach their maximum values (Andrew and Moss, 2002), (Pillay and Wang, 2002). The formula used for WAM is as follows:

$$WAM = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{5.1}$$

For normalized weights, the weighted mean is simply:

$$WAM = \sum_{i=1}^{n} w_i x_i \tag{5.2}$$

where, $w_i$ is the degree of truth of the maximum value of the $i^{th}$ linguistic priority term, and $x_i$ is the risk rank of the maximum value of the $i^{th}$ linguistic priority term. A lower WAM value will indicate that the machinery condition is less risky, while a higher WAM value indicates that the condition of the machinery is at risk, and as such immediate action should be taken.

### 5.3.7 Perform Sensitivity Analysis (Final step)

This subsection employs the sensitivity analysis approach to test how sensitive the model output is to a minor change in the input data. The relative change may be the variation of the parameters of the model or changes in the degrees of belief assigned to the linguistic variables used to describe the parameters of the model. If the methodology is sound and its inference reasoning is logical and robust, then the sensitivity analysis must at least reflect any of the following three axioms stated in Chapter 4, Section 4.2.10 of this thesis.

## 5.4 Test Case

In Chapter 4, the ship crane reliability (SCR) values clearly showed that both the bearing and gearbox are the two major crane components susceptible to failure risk over a period of operations. Therefore, based on the given absolute limits and the sample test results, the operating condition of both port and starboard ship crane bearing and gearbox can be evaluated and monitored.

### 5.4.1 Identification of Grease/Oil Sample Test Results (Step one)

The grease sample test results for the crane bearing and the oil sample test results for the crane gearbox provided are evaluated as follows:

#### 5.4.1.1 Crane bearing grease sample

Tables 5.1 and 5.2 indicate the laboratory test results of a grease sample obtained for port and starboard crane bearing, respectively. Table 5.3 indicates the absolute limits for used grease bearing obtained from a reputable lubricant manufacturer. For the purpose of demonstration in this model, four critical elements (Iron, Tin, Nickel, and Sodium) in the crane bearing grease sample are used.

**Table 5.1:** Critical Wear Elements Test Results for Port Crane Bearing Grease Sample

| Test Element | Used Grease Sample Test Result |
|---|---|
| Iron (Fe) mg/kg | 43 |
| Tin (Sn) mg/kg | 15 |
| Nickel (Ni) mg/k | 5 |
| Sodium (Na) mg/k | 84 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 5.2:** Critical Wear Elements Test Results for Starboard Crane Bearing Grease Sample

| Test Element | Used Grease Sample Test Result |
|---|---|
| Iron (Fe) mg/kg | 69 |
| Tin (Sn) mg/kg | 7 |
| Nickel (Ni) mg/k | 8 |
| Sodium (Na) mg/k | 108 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 5.3:** Absolute Limits for Crane Bearing Used Grease

| Test | Lower Action | Lower Attention | Upper Attention | Upper Action |
|---|---|---|---|---|
| Iron (Fe) | 140 | 375 | 500 | 750 |
| Tin (Sn) | 10 | 29 | 40 | 60 |
| Nickel (Ni) | 1 | 3 | 5 | 8 |
| Sodium (Na) | 35 | 80 | 150 | 200 |

*Source: Hypothetical data from a reputable oil company*

#### 5.4.1.2 Crane gearbox oil sample

Tables 5.4 and 5.5 indicate the laboratory test results of an oil sample obtained for the port and starboard crane gearbox, respectively. Table 5.6 indicates the absolute limits for used oil analysis obtained from a reputable lubricant manufacturer. Only four critical elements (Iron, Tin, Aluminium, and Silicon) in the crane gearbox oil sample are used.

**Table 5.4:** Critical Wear Elements Test Results for Port Crane Gearbox Oil Sample

| Test Element | Used Oil Sample Test Result |
|---|---|
| Iron (Fe) mg/kg | 13 |
| Tin (Sn) mg/kg | 3 |
| Aluminium (Al) m | 4 |
| Silicon (Si) mg/ | 4 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 5.5:** Critical Wear Elements Test Results for Starboard Crane Gearbox Oil Sample

| Test Element | Used Oil Sample Test Result |
|---|---|
| Iron (Fe) mg/kg | 13 |
| Tin (Sn) mg/kg | 1 |
| Aluminium (Al) m | 6 |
| Silicon (Si) mg/kg | 9 |

*Source: Hypothetical data from a reputable oil test laboratory*

**Table 5.6:** Absolute Limits for Crane Gearbox Used Oil

| Test | Lower Action | Lower Attention | Upper Attention | Upper Action |
|---|---|---|---|---|
| Iron (Fe) | 24 | 49 | 60 | 98 |
| Tin (Sn) | 1.5 | 5 | 7 | 9 |
| Aluminium (Al) | 2.5 | 4.5 | 7 | 10 |
| Silicon (Si) | 7 | 15 | 30 | 40 |

*Source: Hypothetical data from a reputable oil company*

### 5.4.2 Test Results Pre-Screening (Step two)

In order to pre-screen the test results obtained for the samples from both port and starboard cranes, a set of rules is generated based on the absolute limits provided in Tables 5.3 and 5.6.

#### 5.4.2.1 Pre-screening of port crane bearing grease sample test results

Iron (Fe) wear element test result:

From Table 5.3, the Lower Action (LA) is set at 140; and Upper Action (UA) is set at 750 for iron (Fe) test element. Also from Table 5.1, the test result value for iron (Fe) is 43. This test result value is not within the LA and UA limits, thus, based on the pre-screening rule in Section 5.3.2, the iron (Fe) test result will fail the pre-screening stage, and then will be returned for re-testing.

In a similar way, the pre-screening of other test elements in the port crane bearing grease sample are assessed and results recorded in Table 5.7.

**Table 5.7:** Port Crane Bearing

| Test Element | Grease Sample Test Result Value | LA Value | UA Value | Pre-screening Status |
|---|---|---|---|---|
| Iron | 43 | 140 | 750 | Fail |
| Tin | 15 | 10 | 60 | Pass |
| Nickel | 5 | 1 | 8 | Pass |
| Sodium | 84 | 35 | 200 | Pass |

*Source: Test case data*

#### 5.4.2.2 Pre-screening of starboard crane bearing grease sample test results

Iron (Fe) wear element test result:

From Table 5.3, the Lower Action (LA) is set at 140; and Upper Action (UA) is set at 750 for iron (Fe) test element. Also, from Table 5.2, the test result value for iron (Fe) is 69. This test result value is not within the LA and UA limits, thus, based on the pre-screening rule, the iron (Fe) test result will fail the pre-screening stage, and then will be returned for re-testing.

In a similar way, the pre-screening of other test elements in the starboard crane bearing grease sample are assessed and results recorded in Table 5.8.

**Table 5.8**: Starboard Crane Bearing

| Test Element | Grease Sample Test Result Value | LA Value | UA Value | Pre-screening Status |
|---|---|---|---|---|
| Iron | 69 | 140 | 750 | Fail |
| Tin | 7 | 10 | 60 | Fail |
| Nickel | 8 | 1 | 8 | Pass |
| Sodium | 108 | 35 | 200 | Pass |

*Source: Test case data*

#### 5.4.2.3 Pre-screening of port crane gearbox oil sample test results

Iron (Fe) wear element test result:

From Table 5.6, the LA is set at 24; and UA is set at 98 for iron (Fe) test element. Also, from Table 5.4, the test result value for iron (Fe) is 13. This test result value is not within the LA and UA limits, thus, based on the pre-screening rule, the iron (Fe) test result will fail the pre-screening stage, and then will be returned for re-testing.

In a similar way, the pre-screening of other test elements in the port crane gearbox oil sample are assessed and results recorded in Table 5.9.

**Table 5.9:** Port Crane Gearbox

| Test Element | Oil Sample Test Result Value | LA Value | UA Value | Pre-screening Status |
|---|---|---|---|---|
| Iron | 13 | 24 | 98 | Fail |
| Tin | 3 | 1.5 | 9 | Pass |
| Aluminium | 4 | 2.5 | 10 | Pass |
| Silicon | 4 | 7 | 40 | Fail |

*Source: Test case data*

#### 5.4.2.4 Pre-screening of starboard crane gearbox oil sample test results

Iron (Fe) wear element test result:

From Table 5.6, the LA is set at 24; and UA is set at 98 for iron (Fe) test element. Also, from Table 5.5, the test result value for iron (Fe) is 13. This test result value is not within the LA and UA limits, thus, based on the pre-screening rule, the iron (Fe) test result will fail the pre-screening stage, and then will be returned for re-testing.

In a similar way, the pre-screening of other test elements in the starboard crane gearbox oil sample are assessed and results recorded in Table 5.10.

**Table 5.10:** Starboard Crane Gearbox

| Test Element | Oil Sample Test Result Value | LA Value | UA Value | Pre-screening Status |
|---|---|---|---|---|
| Iron | 13 | 24 | 98 | Fail |
| Tin | 1 | 1.5 | 9 | Fail |
| Aluminium | 6 | 2.5 | 10 | Pass |
| Silicon | 9 | 7 | 40 | Pass |

*Source: Test case data*

The sample elements test results in Tables 5.7 to 5.10 have either passed or failed the pre-screening process. All the test elements with a failed pre-screening status are returned to the laboratory for a re-test, as indicated in Figure 5.1, while all of the test elements with a passed pre-screening status are used for determining the risk level of the ship crane's components.

### 5.4.3 Development of Fuzzy Membership Function (Step three)

Each of the test elements is described using the following linguistic terms: *Very Low, Low, Moderate, High and Very High.* The interpretation of the linguistic terms describing each scenario has been defined in Table 5.11.

The fuzzy membership functions for the model in this study consist of triangular shapes generated using the linguistic categories identified in the knowledge acquisition stage and applied using the fuzzy Delphi method (Bojadziev & Bojadziev, 1995). The membership function for each linguistic terms can be obtained using the sample test results shown in Tables 5.1 and 5.2 for port and starboard crane bearing grease samples; Tables 5.4 and 5.5 for port and starboard crane gearbox oil samples; and by applying the same rules used in Chapter 4. These are graphically illustrated in the Figures given in Appendix 5A. Their corresponding belief degrees are shown in Tables 5.12 to 5.15.

**Table 5.11:** Description for Test Elements and General Interpretation

| **Linguistic Term for Test Elements** | **General Interpretation** |
|---|---|
| Very Low | Wear particles present in small quantities. Acceptable amount of normal wear particles. |
| Low | Wear particles present in small quantities. Acceptable amount of normal wear particles. |
| Moderate | Wear particles present in medium quantities. Acceptable amount of normal wear particles. |
| High | Wear particles present in high quantities. Unacceptable amount of normal wear particles. |
| Very High | The wear metals content is higher than normal. The crane should be stopped for investigation. |

*Source: Test case data*

**Table 5.12:** Fuzzy Set for Port Crane Bearing Grease Sample Test Elements

| **Test Element** | **Belief Degrees Associated with the Linguistic Terms** |
|---|---|
| Tin (Sn) | {(0.75, Very Low), (0.25, Low), (0, Moderate), (0, High), (0, Very High)} |
| Nickel (Ni) | {(0, Very Low), (0, Low), (0.875, Moderate), (0.125, High), (0, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.9, Low), (0.1, Moderate), (0, High), (0, Very High)} |

*Source: Test case data*

**Table 5.13**: Fuzzy Set for Starboard Crane Bearing Grease Sample Test Elements

| **Test Element** | **Belief Degrees Associated with the Linguistic Terms** |
|---|---|
| Nickel (Ni) | {(0, Very Low), (0, Low), (0, Moderate), (0, High), (1, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.3, Low), (0.7, Moderate), (0, High), (0, Very High)} |

*Source: Test case data*

**Table 5.14:** Fuzzy Set for Port Crane Gearbox Oil Sample Test Elements

| **Test Element** | **Belief Degrees Associated with the Linguistic Terms** |
|---|---|
| Tin (Sn) | {(0.333, Very Low), (0.667, Low), (0, Average), (0, High), (0, Very High)} |
| Aluminium (Al) | {(0, Very Low), (1, Low), (0, Moderate), (0, High), (0, Very High)} |

*Source: Test case data*

**Table 5.15:** Fuzzy Set for Starboard Crane Gearbox Oil Sample Test Elements

| Test Element | Belief Degrees Associated with the Linguistic Terms |
|---|---|
| Aluminium (Al) | {(0, Very Low), (0, Low), (1, Moderate), (0, High), (0, Very High)} |
| Silicon (Si) | {(0.875, Very Low), (0.125, Low), (0, Moderate), (0, High), (0, Very High)} |

*Source: Test case data*

### 5.4.4 Development of Fuzzy Rule Base (Step four)

To develop the fuzzy rule base, the five linguistic terms (Very Low, Low, Moderate, High and Very High) are first graded (shown in Table 5.16) using the four output sample grades (i.e. Normal, Caution, Attention, and Critical). These output grades are identified as priority levels of alert for each of the linguistic terms associated with the sample elements. The highest degree of the individual linguistic terms of the sample elements is assigned with the corresponding grade (Table 5.16) as the priority level of alert.

Consider the following examples in Appendix 5B, Table 1-5B:

Rule number 1 - the linguistic terms for sample elements are ‘Very Low’, ‘Very Low’, and ‘Very Low’. The highest degree of individual linguistic term is ‘Very Low’ and, from Table 5.16, the grade assigned to ‘Very Low’ is Normal. Thus, the priority level of attention is shown as Normal.

Rule number 2 - the linguistic terms for sample elements are ‘Very Low’, ‘Very Low’, and ‘Low’. The highest degree of individual linguistic term is ‘Low’ and, from Table 5.16, the grade assigned to ‘Low’ is Normal. Thus, the priority level of attention is shown as Normal.

Rule number 3 - the linguistic terms for sample elements are ‘Very Low’, ‘Very Low’, and ‘Moderate’. The highest degree of individual linguistic term is ‘Moderate’ and, from Table 5.16, the grade assigned to ‘Moderate’ is Caution. Thus, the priority level of attention is shown as Caution.

Rule number 4 - the linguistic terms for sample elements are ‘Very Low’, ‘Very Low’, and ‘High’. The highest degree of individual linguistic term is ‘High’ and, from Table 5.16, the grade assigned to ‘High’ is Attention. Thus, the priority level of attention is shown as Attention.

Rule number 5 - the linguistic terms for sample elements are ‘Very Low’, ‘Very Low’, and ‘Very High’. The highest degree of individual linguistic term is ‘Very High’ and, from Table 5.16, the grade assigned to ‘Very High’ is Critical. Thus, the priority level of attention is shown as Critical.

In view of the fact that there are three elements (A, B, and C) associated with the five linguistic terms, a total of 125 (5 x 5 x 5) rules were developed, as shown in Table 1-5B in Appendix 5B.

Also, consider the following examples in Appendix 5B, Table 2-5B:

Rule number 1 - the linguistic terms for sample elements are 'Very Low' and 'Very Low'. The highest degree of individual linguistic term is 'Very Low' and, from Table 5.16, the grade assigned to 'Very Low' is Normal. Thus, the priority level of attention is shown as Normal.

Rule number 2 - the linguistic terms for sample elements are 'Very Low', and 'Low'. The highest degree of individual linguistic term is 'Low' and, from Table 5.16, the grade assigned to 'Low' is Normal. Thus, the priority level of attention is shown as Normal.

Rule number 3 - the linguistic terms for sample elements are 'Very Low', and 'Moderate'. The highest degree of individual linguistic term is 'Moderate' and, from Table 5.16, the grade assigned to 'Moderate' is Caution. Thus, the priority level of attention is shown as Caution.

Rule number 4 - the linguistic terms for sample elements are 'Very Low', and 'High'. The highest degree of individual linguistic term is 'High' and, from Table 5.16, the grade assigned to 'High' is Attention. Thus, the priority level of attention is shown as Attention.

Rule number 5 - the linguistic terms for sample elements are 'Very Low', and 'Very High'. The highest degree of individual linguistic term is 'Very High' and, from Table 5.16, the grade assigned to 'Very High' is Critical. Thus, the priority level of attention is shown as Critical.

In view of the fact that there are two elements (A, and B) associated with the five linguistic terms, a total of 25 (5 x 5) rules were developed, as shown in Table 2-5B in Appendix 5B.

It is worth mentioning that though three test sample elements were used in developing the 125 (5 x 5 x 5) rules, and two test sample elements used in developing the 25 (5 x 5) rules in the test case using the fuzzy rule based technique, by using the same technique, a model with fewer or more than three test sample elements can be designed to meet the industrial need.

**Table 5.16:** Linguistic Term Grades & Risk Ranking

| Linguistic Term | Grade | Risk Ranking |
|---|---|---|
| Very Low | Normal | 1 |
| Low | Normal | 1 |
| Moderate | Caution | 2 |
| High | Attention | 3 |
| Very High | Critical | 4 |

*Source: Test case data*

### 5.4.5 Determination of Risk Levels for the Sample Test Elements of each Crane Component and the Acquirement of its Fuzzy Conclusion (Step five)

In order to obtain a risk ranking, two steps are required. Firstly, the linguistic priority terms and the membership values reflecting the risk levels for the sample test element of each crane component should be carefully decided. Secondly, the fuzzy set conclusion of each crane component will be obtained based on the fuzzy rule base using the 'min-max' approach. Since this research only considers three sample test elements for each crane component (bearing and gearbox), for both port and starboard of the ship, the fuzzy set obtained in Tables 5.12, 5.13, 5.14, and 5.15 will be used to determine its fuzzy conclusion.

#### 5.4.5.1 Risk level for port crane bearing grease sample test elements

By applying the 'min-max' approach, the set of fuzzy conclusions of the port crane bearing grease sample test element in Table 5.12 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Sn = Very Low 0.75, Ni = Moderate 0.875, and Na = Low 0.9, then based on rule 12 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.
   (2) If Sn = Very Low 0.75, Ni = Moderate 0.875, and Na = Moderate 0.1, then based on rule 13 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.
   (3) If Sn = Very Low 0.75, Ni = High 0.125, and Na = Low 0.9, then based on rule 17 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.
   (4) If Sn = Very Low 0.75, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 18 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.
   (5) If Sn = Low 0.25, Ni = Moderate 0.875, and Na = Low 0.9, then based on rule 37 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.
   (6) If Sn = Low 0.25, Ni = Moderate 0.875, and Na = Moderate 0.1, then based on rule 38 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.
   (7) If Sn = Low 0.25, Ni = High 0.125, and Na = Low 0.9, then based on rule 42 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(8) If Sn = Low 0.25, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 43 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.75, Ni = Moderate 0.875, and Na = Low 0.9. Therefore, the minimum value of Sn, Ni, and Na is 0.75, which is associated with the linguistic priority term CAUTION, according to the fuzzy rule developed. The minimum values of the other seven combinations can be determined in a similar way, as shown in Table 5.17.

**Table 5.17:** The Minimum Value of each Combination for Port Crane Bearing

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | Caution 0.75 | 2 | Caution 0.1 | 3 | Attention 0.125 | 4 | Attention 0.1 |
| 5 | Caution 0.25 | 6 | Caution 0.1 | 7 | Attention 0.125 | 8 | Attention 0.1 |

*Source: Test case data*

iii. Determine the maximum value of the minimum values obtained from step 2 that has the same category of linguistic priority term.

In the first scenario, there are eight combinations and two different categories of linguistic priority terms, CAUTION and ATTENTION. The membership values in the CAUTION category are 0.75, 0.1, 0.25, and 0.1, respectively. Therefore, the maximum membership value is 0.75, as shown in Table 5.18. Likewise, the values in the ATTENTION category in the 3rd, 4th, 7th and 8th combinations are 0.125. Thus, the maximum membership value in the ATTENTION category is 0.125, also shown in Table 5.18.

**Table 5.18:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Caution | 0.75 |
| Attention | 0.125 |

*Source: Test case data*

5.4.5.2 Risk level for starboard crane bearing grease sample test elements

By applying the 'min-max' approach, the set of fuzzy conclusions of the starboard crane bearing grease sample test element in Table 5.13 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Ni = Very High 1, and Na = Low 0.3, then based on rule 22 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(2) If Ni = Very High 1, and Na = Moderate 0.7, then based on rule 23 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Ni = Very High 1 and Na = Low 0.3. Therefore, the minimum value of Ni and Na is 0.3, which is associated with the linguistic priority term CRITICAL, according to the fuzzy rule developed. The minimum values of the other combination can be determined in a similar way, as shown in Table 5.19.

**Table 5.19:** The Minimum Value of each Combination for Starboard Crane Bearing

| | | | |
|---|---|---|---|
| 1 | Critical 0.3 | 2 | Critical 0.7 |

*Source: Test case data*

iii. Determine the maximum value of the minimum values obtained from step 2 that has the same category of linguistic priority terms.

In the first scenario, there are two combinations and one category of linguistic priority terms, CRITICAL. The membership values in the CRITICAL category are 0.3 and 0.7. Therefore, the maximum membership value is 0.7.

5.4.5.3 Risk level for port crane gearbox oil sample test elements

By applying the 'min-max' approach, the set of fuzzy conclusions of port crane gearbox oil sample test element in Table 5.14 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Sn = Very Low 0.333, and Al = Low 1, then based on rule 2 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.

(2) If Sn = Low 0.667, and Al = Low 1, then based on rule 7 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.333, and Al = Low 1. Therefore, the minimum value of Sn and Al is 0.333, which is associated with the linguistic priority term NORMAL, according to the fuzzy rule developed. The minimum values of the other combination can be determined in a similar way, as shown in Table 5.20.

**Table 5.20:** The Minimum Value of each Combination for Port Crane Gearbox

| | | | |
|---|---|---|---|
| 1 | Normal 0.333 | 2 | Normal 0.667 |

*Source: Test case data*

iii. Determine the maximum value of the minimum values obtained from step 2 that has the same category of linguistic priority term.

In the first scenario, there are two combinations and one category of linguistic priority terms, NORMAL. The membership values in the NORMAL category are 0.333 and 0.667. Therefore, the maximum membership value is 0.667.

5.4.5.4 Risk level for starboard crane gearbox oil sample test elements

By applying the 'min-max' approach, the set of fuzzy conclusions of starboard crane gearbox oil sample test element in Table 5.15 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Al = Moderate 1, and Si = Very Low 0.875, then based on rule 11 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.
   (2) If Al = Moderate 1, and Si = Low 0.125, then based on rule 12 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Al = Moderate 1, and Si = Very Low 0.875. Therefore, the minimum value of Al and Si is 0.875, which is associated with the linguistic priority term CAUTION, according to the fuzzy rule developed. The minimum values of the other combination can be determined in a similar way, as shown in Table 5.21.

**Table 5.21:** The Minimum Value of each Combination for Starboard Crane Gearbox

| | | | |
|---|---|---|---|
| 1 | Caution 0.875 | 2 | Caution 0.125 |

*Source: Test case data*

iii. Determine the maximum value of the minimum values obtained from step 2 that has the same category of linguistic priority term.

In the first scenario, there are two combinations and one category of linguistic priority terms, CAUTION. The membership values in the CAUTION category are 0.875 and 0.125. Therefore, the maximum membership value is 0.875.

**Table 5.22:** The Set of Fuzzy Conclusions of the Ship's Crane

| Ship Crane Components | Set of Fuzzy Conclusions |
|---|---|
| Port crane bearing | Caution 0.75, Attention 0.125 |
| Starboard crane bearing | Critical 0.7 |
| Port crane gearbox | Normal 0.667 |
| Starboard crane gearbox | Caution 0.875 |

*Source: Test case data*

### 5.4.6 The Defuzzification Process (Step six)

By applying Equation (5.2) in the defuzzification process and the risk ranking for the linguistic term grades given in Table 5.16, the risk values (RV) for the set of fuzzy conclusions in Table 5.22 can be obtained. The components with higher risk values are considered to be critical.

For example, the risk value for the port crane bearing can be determined as follows:

RV = (2 x 0.75) + (3 x 0.125) = **1.875**

In a similar way, the RV for the starboard crane bearing, port and starboard crane gearboxes are obtained as shown in Table 5.23.

From Table 5.23, it can be noted that the risk value for the starboard crane bearing is 2.8 (higher risk value). Therefore, the ship starboard crane bearing is considered as being critical. With this information, the maintenance engineer on board the ship can stop the starboard crane (if it is under operation) for investigation, thus preventing any major damage to the crane.

**Table 5.23**: The Ship Crane Components Risk Values

| Ship Crane Components | Risk Value |
|---|---|
| Port crane bearing | 1.875 |
| Starboard crane bearing | 2.8 |
| Port crane gearbox | 0.667 |
| Starboard crane gearbox | 1.75 |

*Source: Test case data*

### 5.4.7 Sensitivity Analysis (Final step)

Sensitivity analysis is performed to assess the robustness and logicality of the delivery of the analysis results obtained in Section 5.4.6. This is achieved by utilising the three axioms introduced in Section 4.2.10. The implementation of the axioms will help to identify the most important priority level that should be given attention in order to improve the ship's crane bearing and gearbox operational uncertainties.

To perform the analysis, the input data in Tables 5.12 to 5.15 associated with the highest preference linguistic values of all the lower level criteria are decreased by a factor of 10%, 20%, and 30% respectively, whilst simultaneously increasing the input data of the lowest preference linguistic values of each of the criteria at the lower level. In light of the above, decreasing the input data of the highest preference linguistic value $(\beta_H)$ of a given criterion by a factor of $(x)$ means the input data of the lowest preference linguistic value will be increased by the same factor.

If $(\beta_H)$ is less than $(x)$, then the remaining belief degree (i.e. $x - \beta_H)$ can be taken from the next linguistic value, until $(x)$ is consumed completely in a structured and systematic process. Accordingly, the decrement values are as shown in Tables 5.24 - 5.35.

#### 5.4.7.1 Decrement by 0.1

**Table 5.24:** Decrement of Port Crane Bearing Grease Sample Test Elements by 0.1

| **Test Elements** | **The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.1** |
|---|---|
| Tin (Sn) | {(0.65, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.1, Very High)} |
| Nickel (Ni) | {(0, Very Low), (0, Low), (0.775, Moderate), (0.125, High), (0.1, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.8, Low), (0.1, Moderate), (0, High), (0.1, Very High)} |

*Source: Test case data*

**Table 5.25:** Decrement of Starboard Crane Bearing Grease Sample Test Elements by 0.1

| **Test Elements** | **The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.1** |
|---|---|
| Nickel (Ni) | {(0.1, Very Low), (0, Low), (0, Moderate), (0, High), (0.9, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.2, Low), (0.7, Moderate), (0, High), (0.1, Very High)} |

*Source: Test case data*

**Table 5.26:** Decrement of Port Crane Gearbox Oil Sample Test Elements by 0.1

| **Test Elements** | **The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.1** |
|---|---|
| Tin (Sn) | {(0.233, Very Low), (0.667, Low), (0, Moderate), (0, High), (0.1, Very High)} |
| Aluminium (Al) | {(0, Very Low), (0.9, Low), (0, Moderate), (0, High), (0.1, Very High)} |

*Source: Test case data*

**Table 5.27:** Decrement of Starboard Crane Gearbox Oil Sample Test Elements by 0.1

| **Test Elements** | **The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.1** |
|---|---|
| Aluminium (Al) | {(0, Very Low), (0, Low), (0.9, Moderate), (0, High), (0.1, Very High)} |
| Silicon (Si) | {(0.775, Very Low), (0.125, Low), (0, Moderate), (0, High), (0.1, Very High)} |

*Source: Test case data*

#### 5.4.7.2 Decrement by 0.2

**Table 5.28:** Decrement of Port Crane Bearing Grease Sample Test Elements by 0.2

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.2 |
|---|---|
| Tin (Sn) | {(0.55, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.2, Very High)} |
| Nickel (Ni) | {(0, Very Low), (0, Low), (0.675, Moderate), (0.125, High), (0.2, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.7, Low), (0.1, Moderate), (0, High), (0.2, Very High)} |

*Source: Test case data*

**Table 5.29:** Decrement of Starboard Crane Bearing Grease Sample Test Elements by 0.2

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.2 |
|---|---|
| Nickel (Ni) | {(0.2, Very Low), (0, Low), (0, Moderate), (0, High), (0.8, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.1, Low), (0.7, Moderate), (0, High), (0.2, Very High)} |

*Source: Test case data*

**Table 5.30:** Decrement of Port Crane Gearbox Oil Sample Test Elements by 0.2

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.2 |
|---|---|
| Tin (Sn) | {(0.133, Very Low), (0.667, Low), (0, Moderate), (0, High), (0.2, Very High)} |
| Aluminium (Al) | {(0, Very Low), (0.8, Low), (0, Moderate), (0, High), (0.2, Very High)} |

*Source: Test case data*

**Table 5.31:** Decrement of Starboard Crane Gearbox Oil Sample Test Elements by 0.2

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.2 |
|---|---|
| Aluminium (Al) | {(0, Very Low), (0, Low), (0.8, Moderate), (0, High), (0.2, Very High)} |
| Silicon (Si) | {(0.675, Very Low), (0.125, Low), (0, Moderate), (0, High), (0.2, Very High)} |

*Source: Test case data*

#### 5.4.7.3 Decrement by 0.3

**Table 5.32:** Decrement of Port Crane Bearing Grease Sample Test Elements by 0.3

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.3 |
|---|---|
| Tin (Sn) | {(0.45, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.3, Very High)} |
| Nickel (Ni) | {(0, Very Low), (0, Low), (0.575, Moderate), (0.125, High), (0.3, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.6, Low), (0.1, Moderate), (0, High), (0.3, Very High)} |

*Source: Test case data*

**Table 5.33:** Decrement of Starboard Crane Bearing Grease Sample Test Elements by 0.3

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.3 |
|---|---|
| Nickel (Ni) | {(0.3, Very Low), (0, Low), (0, Moderate), (0, High), (0.7, Very High)} |
| Sodium (Na) | {(0, Very Low), (0, Low), (0.7, Moderate), (0, High), (0.3, Very High)} |

*Source: Test case data*

**Table 5.34:** Decrement of Port Crane Gearbox Oil Sample Test Elements by 0.3

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.3 |
|---|---|
| Tin (Sn) | {(0.033, Very Low), (0.667, Low), (0, Moderate), (0, High), (0.3, Very High)} |
| Aluminium (Al) | {(0, Very Low), (0.7, Low), (0, Moderate), (0, High), (0.3, Very High)} |

*Source: Test case data*

**Table 5.35:** Decrement of Starboard Crane Gearbox Oil Sample Test Elements by 0.3

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.3 |
|---|---|
| Aluminium (Al) | {(0, Very Low), (0, Low), (0.7, Moderate), (0, High), (0.3, Very High)} |
| Silicon (Si) | {(0.575, Very Low), (0.125, Low), (0, Moderate), (0, High), (0.3, Very High)} |

*Source: Test case data*

#### 5.4.7.4 Determination of risk level and fuzzy conclusions from the decrement of 0.1, 0.2 and 0.3

By applying the ‘min-max’ approach described in Section 5.4.5, membership function values are listed according to the rules developed for the decrement values obtained in Tables 5.24 to 5.35. The corresponding minimum values of the combinations for each of the scenario are also obtained as described in Appendices 5C, 5D, and 5E. The maximum values associated with the same category of linguistic priority terms for each of the scenarios are determined as shown in Tables 5.36 to 5.39, while Table 5.40 shows the set of fuzzy conclusions of the ship’s crane derived as the result of the decrement. It is worth mentioning that all the results obtained remain in harmony with both Axioms 1 and 2.

**Table 5.36:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Decrement of Port Crane Bearing Grease Sample Elements

| Category of linguistic priority terms | Maximum values by decrement of 0.1 | Maximum values by decrement of 0.2 | Maximum values by decrement of 0.3 |
|---|---|---|---|
| Caution | 0.65 | 0.55 | 0.45 |
| Attention | 0.125 | 0.125 | 0.125 |
| Critical | 0.1 | 0.2 | 0.3 |

*Source: Test case data*

**Table 5.37:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Decrement of Starboard Crane Bearing Grease Sample Elements

| Category of linguistic priority terms | Maximum values by decrement of 0.1 | Maximum values by decrement of 0.2 | Maximum values by decrement of 0.3 |
|---|---|---|---|
| Normal | 0.1 | 0.1 | N/A |
| Caution | 0.1 | 0.2 | 0.3 |
| Critical | 0.7 | 0.7 | 0.7 |

*Source: Test case data*

**Table 5.38:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Decrement of Port Crane Gearbox Oil Sample Elements

| Category of linguistic priority terms | Maximum values by decrement of 0.1 | Maximum values by decrement of 0.2 | Maximum values by decrement of 0.3 |
|---|---|---|---|
| Normal | 0.667 | 0.667 | 0.667 |
| Critical | 0.1 | 0.2 | 0.3 |

*Source: Test case data*

**Table 5.39:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Decrement of Starboard Crane Gearbox Oil Sample Elements

| Category of linguistic priority terms | Maximum values by decrement of 0.1 | Maximum values by decrement of 0.2 | Maximum values by decrement of 0.3 |
|---|---|---|---|
| Caution | 0.775 | 0.675 | 0.575 |
| Critical | 0.1 | 0.2 | 0.3 |

*Source: Test case data*

**Table 5.40:** The Set of Fuzzy Conclusions of the Ship's Crane from Decrement values

| Ship Crane | Set of Fuzzy Conclusions | | |
|---|---|---|---|
| | **Decrement by 0.1** | **Decrement by 0.2** | **Decrement by 0.3** |
| Port crane bearing | Caution 0.65, Attention 0.125, Critical 0.1, | Caution 0.55, Attention 0.125, Critical 0.2, | Caution 0.45, Attention 0.125, Critical 0.3, |
| Starboard crane bearing | Normal 0.1, Caution 0.1, Critical 0.7, | Normal 0.1, Caution 0.2, Critical 0.7, | Caution 0.3, Critical 0.7, |
| Port crane gearbox | Normal 0.667, Critical 0.1 | Normal 0.667, Critical 0.2 | Normal 0.667, Critical 0.3 |
| Starboard crane gearbox | Caution 0.775, Critical 0.1 | Caution 0.675, Critical 0.2 | Caution 0.575, Critical 0.3 |

*Source: Test case data*

5.4.7.5 Risk values from the decremented set of fuzzy conclusions (0.1, 0.2, and 0.3)

The risk values for the decremented set of fuzzy conclusions are determined using the defuzzification process described in Section 5.4.6. For example, the risk value from the port crane bearing set of fuzzy conclusions is obtained as follows:

<u>10% decrement</u>

$$Caution\ \frac{0.65}{0.65+0.125+0.1},\ Attention\ \frac{0.125}{0.65+0.125+0.1},\ Critical\ \frac{0.1}{0.65+0.125+0.1}$$

$$RV = 2 \times \frac{0.65}{0.65+0.125+0.1} + 3 \times \frac{0.125}{0.65+0.125+0.1} + 4 \times \frac{0.1}{0.65+0.125+0.1} = 2.366$$

Similarly, the RV for other set of fuzzy conclusions in Table 5.40 is obtained as shown in Table 5.41. See Appendix 5F for detail calculations.

**Table 5.41:** Risk Values from the Decremented Set of Fuzzy Conclusions

| Ship Crane Component | Risk Values | | |
|---|---|---|---|
| | **Decrement by 0.1** | **Decrement by 0.2** | **Decrement by 0.3** |
| Port crane bearing | 2.366 | 2.594 | 2.822 |
| Starboard crane bearing | 3.441 | 3.3 | 3.4 |
| Port crane gearbox | 1.389 | 1.689 | 1.929 |
| Starboard crane gearbox | 2.226 | 2.454 | 2.682 |

*Source: Test case data*

From Table 5.41, it can be noted that the starboard crane bearing has the highest risk values, indicating a similar outcome obtained when the risk value was determined in Section 5.4.6.

Axiom 3 in Section 4.2.10 can be examined by comparing the preference degrees of the risk attributes for analysis in a transparent manner. In order to determine if the model aligned with axiom 3, two elements (i.e. Tin and Sodium) out of the three test elements of the analysis from the port crane bearing oil sample (Table 5.12) are selected and their input data decreased by 30%, as shown in Table 5.42.

**Table 5.42:** Using Two Test Elements for Decrement of Port Crane Bearing by 0.3

| Test Elements | The degree of belief associated with the highest preference linguistic variable is decreased and simultaneously the degree of belief associated with the lowest preference linguistic variable is increased by 0.3 |
|---|---|
| Tin (Sn) | {(0.45, Very Low), (0.25, Low), (0, Moderate), (0, High), (0.3, Very High)} |
| Sodium (Na) | {(0, Very Low), (0.6, Low), (0.1, Moderate), (0, High), (0.3, Very High)} |

By applying the 'min-max' approach, the set of fuzzy conclusions of the two test elements for decreasing port crane bearing grease sample in Table 5.42 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Sn = Very Low 0.45, and Na = Low 0.6, then based on rule 2 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.
   (2) If Sn = Very Low 0.45, and Na = Moderate 0.1, then based on rule 3 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.
   (3) If Sn = Very Low 0.45, and Na = Very High 0.3, then based on rule 5 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (4) If Sn = Low 0.25, and Na = Low 0.6, then based on rule 7 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.
   (5) If Sn = Low 0.25, and Na = Moderate 0.1, then based on rule 8 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.
   (6) If Sn = Low 0.25, and Na = Very High 0.3, then based on rule 10 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (7) If Sn = Very High 0.3, and Na = Low 0.6, then based on rule 22 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (8) If Sn = Very High 0.3, and Na = Moderate 0.1, then based on rule 23 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (9) If Sn = Very High 0.3, and Na = Very High 0.3, then based on rule 25 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.45, and Na = Low 0.6. Therefore, the minimum value of Sn and Na is 0.45, which is associated with the linguistic priority term NORMAL, according to the fuzzy rule developed. The minimum values of the other eight combinations can be determined in a similar way, as shown in Table 5.43.

**Table 5.43:** The Minimum Value of each Combination for Port Crane Bearing

| | | | | | |
|---|---|---|---|---|---|
| 1 | Normal 0.45 | 2 | Caution 0.1 | 3 | Critical 0.3 |
| 4 | Normal 0.25 | 5 | Caution 0.1 | 6 | Critical 0.25 |
| 7 | Critical 0.3 | 8 | Critical 0.1 | 9 | Critical 0.3 |

iii. Determine the maximum value of the minimum values obtained from step 2 that has the same category of linguistic priority term.

In the first scenario, there are nine combinations and three different categories of linguistic priority terms, NORMAL, CAUTION, and CRITICAL. The membership values in the NORMAL category are 0.45 and 0.25, respectively. Therefore, the maximum membership value is 0.45, as shown in Table 5.44. Likewise, the maximum membership values in the CAUTION and CRITICAL categories are determined, as shown in Table 5.44.

**Table 5.44:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Normal | 0.45 |
| Caution | 0.1 |
| Critical | 0.3 |

*Source: Test case data*

5.4.7.6 Risk values from the decremented set of fuzzy conclusions of the Port Bearing

The risk values for the decremented set of fuzzy conclusions from the two elements of the port crane bearing is obtained as follows:

$$Normal\ \frac{0.45}{0.45+0.1+0.3},\ Caution\ \frac{0.1}{0.45+0.1+0.3},\ Critical\ \frac{0.3}{0.45+0.1+0.3}$$

$$RV = 1 \times \frac{0.45}{0.45+0.1+0.3} + 2 \times \frac{0.1}{0.45+0.1+0.3} + 4 \times \frac{0.3}{0.45+0.1+0.3} = 2.171$$

Notice that when the input data associated with the highest preference linguistic values of the ship port crane bearing fuzzy sets of the three test elements was decreased by 30%, the risk value of the crane component (i.e. failure risk) was evaluated as 2.822, as indicated in Table 5.41. However, by selecting two elements (i.e. Tin and Sodium) out of the three test elements of the analysis from the port crane bearing oil sample (Table 5.12) and decreasing the input data by the same amount of 30%, the risk value obtained is 2.171. Given that 2.171 is less than 2.822, it can be claimed that the investigation of the model is validated to be sound and aligned with Axiom 3.

## 5.5 Discussions

This research has demonstrated how to start with a simple dynamic model and generate a rule-based diagnostic model. Grease / oil analysis has proven to be a useful tool to evaluate grease and bearing, as well as oil and gearbox condition, respectively. Different situations and influencing factors for wear, contamination, and grease condition have shown complex lucidities between the grease analysis results and their practical meaning. This leads to the deduction that observing and interpreting these factors with expert knowledge can allow proactive maintenance strategies to be applied in a reasonable approach for grease-lubricated components. Understanding the oil sample data and realizing how to properly apply alarm limits can significantly reduce the downtime of marine crane bearing and gearbox failure.

The approach utilised in this research is non-traditional and, according to Ramezani and Memariani (2011), non-traditional modelling approaches may have the following benefits:

1. Rule-based knowledge representation, together with the extraction of rule, offers a means of integrating data-driven modelling with physics-based modelling.
2. A rule-based model is complementary with human investigative reasoning as well as human errors, thereby allowing industrial experts to contribute directly to the model building.
3. A rule-base is transparent to the user. The way the decision is made can be plainly elucidated so that users can quickly gain trust in the system. This is vital in safety-critical machinery like ship cranes where human lives are at risk.

The approach here involves first identifying through literature review the key system variables that affect ship cranes, and then developing a set of decision rules relating to these key variables. This provides a powerful tool for knowledge specification and effective condition monitoring of ship cranes.

From the diagnostic risk assessment tool, a NORMAL sample status indicates that the physical properties of the lubricant are within acceptable limits and no signs of excessive contamination/wear are present. ATTENTION indicates that results are outside acceptable ranges but not critical, although caution, re-sampling, and increased monitoring is advised. The CRITICAL status requires immediate corrective action to prevent significant major damage/failure in service.

Failure to detect potential lube oil/equipment failure and wear may lead to poor performance and even cause expensive damage and, in some cases, loss of business. On the other hand, inaccurate diagnosis of equipment failure may cause unnecessary interruption to an entire business. Either case can result in significant monetary loss. Oil analysis is an increasingly popular condition-monitoring tool, meaning this developed diagnostic risk assessment tool is needed and, if adopted, will improve operating efficiency and reduce failures of ship cranes.

## 5.6 Conclusion

The main aim of this chapter is to develop an expert system that will diagnose early signs of problems in ship cranes by utilising oil-sampling analysis. This has been achieved by the design concept of a logic rule-based system that provides risk levels diagnosis to enable grease/oil samples test results to be processed for the diagnosis of the ship cranes, using grease/oil-sampling analysis. A fuzzy modelling approach utilizing IF-THEN rules and its usefulness in condition monitoring of applications was illustrated in this chapter. The model showed how to build a bridge between the qualitative reliability analysis of the design phase and the diagnosis in the usage phase. The goal of producing a diagnosis model for a ship crane was satisfied. The outcome of this methodology is a rule-based model, which is a diagnosis tool that helps the maintenance crew prevent a ship crane failure with a reduced number of investigations. The tool allows the maintenance crew to make decisions that are more efficient when trying to diagnose fault in a crane, thus augmenting their competences. The generated alert risk levels in the tool helps in addressing some of the concerns raised in the introduction. It provides the maintenance crew with a map that allows recognition of the failing components, and informs them of which ones' need replacing.

This methodology shows how, with several systematic steps, a rule based diagnostic tool can be generated. This leads to the conclusion that this process can be automated and undeniably, that is the goal of this research. The diagnostic tool accuracy can be improved if a comprehensive data is available for a specific crane, as well as all the properties of the lubricant being used by the specified crane, in addition to monitoring trends. Such data can then be incorporated into this rule-based tool. A broader accurate diagnosis can be achieved if a wider range of data is available. These can be achieved if original equipment manufacturers and oil sampling laboratories are willing to supply this information, which is often very difficult to obtain.

# Chapter 6

# Application of a Multiple Attribute Group Decision Making (MAGDM) Model for Selection of the best Maintenance Strategy for Marine and Offshore Machinery based on Fuzzy Technique for Order Preference by Similarity to Ideal Situation (FTOPSIS)

**Summary**

This chapter proposes a strategic fuzzy multi-attribute decision making methodology for the concise and straightforward selection of an appropriate maintenance strategy. The decision support structure allows the use of multiple decision makers to incorporate and aggregate their subjective opinions transparently. In the analysis, a Fuzzy Technique for Order Preference by Similarity to Ideal Situation is employed to rank the maintenance strategies with respect to costs and benefits for their subsequent implementation.

## 6.1 Introduction

In 1979, the Massachusetts Institute of Technology (MIT) carried out an extraordinary milestone study in which it estimated that over $200 billion was spent annually on maintenance in North America. Moreover, approximately one third of this expenditure was determined to be unnecessary. Maintenance, and in particular the effect of mal-lubrication, is still one of the few remaining areas of a company's expenditure that can be significantly improved upon. Many modern engines contain a number of complex systems and thus require a variety of maintenance procedures for reliable, cost effective operation. The increasing cost, complexity of maintenance, other uncertainties, and their effect on production has initiated a need for adequate and proper planning, management, and omission of the maintenance process (Toms and Toms, 2008). Almost all modern maintenance programs include a variation of one or more of the following general maintenance procedures: Run-to-Failure Maintenance, Preventive Maintenance, Condition-Based Maintenance, and Reliability Centred Maintenance.

Therefore, the assessment of the cost of the planned maintenance (PM) strategies may require an advanced cost benefit analysis and a powerful tool for risk management methodology to aid in decision making. Decision making can be characterised as a process of selecting a highly sufficient alternative from a set of alternatives to attain a goal. Many decisions involve uncertainty. In order to overcome the uncertainty and risk that threatens the maintenance, it is important to design a robust expert system that will cater for all the above maintenance procedures, which is one of the strategies developed in Chapter 4 and Chapter 5.

In this chapter, decision makers' opinions will be expressed through a process of fuzzy multi-attribute group decision making and aggregated to obtain the performance rating with respect to all of the attributes for each maintenance procedure alternative. Decision makers' fuzzy decision matrixes are used and converted into an aggregated decision matrix to determine the most preferable choice among all possible alternatives. Fuzzy multi-attribute decision making is a tool that is suitable for group decision making under a fuzzy environment (Li, 2007). As a result, the purpose of using FMADM in this chapter is to aggregate and synthesise opinions of experts, thus, guiding them in decision making when they are planning to implement a cost effective maintenance investment.

There are a number of Multiple Criteria Decision Making methods in literature, such as Fuzzy Technique for Order Preference by Similarity to Ideal Situation (Chen, 2000). A novel method for the MAGDM will be proposed in this chapter. In this method, the linguistic terms will be used during the evaluation process, and then FTOPSIS is used to rank the alternatives. This novel MAGDM technique can efficiently resolve the fuzzy information by decreasing its uncertainty level, is capable of reducing the computation time, and can provide reasonable and robust ranking results.

## 6.2 Methodology

The proposed methodology and hierarchical structure describing the decision making process of selecting an ideal maintenance strategy for marine and offshore machinery is graphically illustrated in Figure 6.1. The first stage is the identification of decision making alternatives for marine equipment maintenance. The decision alternatives and evaluation criteria are literature-based and have been derived from various literature reviews. The evaluation process is conducted by decision analysts based on their subjective knowledge and judgment on marine equipment maintenance practice.

The second stage in the methodology is the identification of the evaluation criteria for the identified proto-type maintenance strategies. In the third stage, the AHP methodology is applied to obtain the importance weights of the evaluation criteria. In the fourth stage, FTOPSIS is applied to obtain performance ratings of the various decision alternatives. The importance weights obtained through the AHP are incorporated into the FTOPSIS analysis to obtain performance ratings of the decision alternatives.

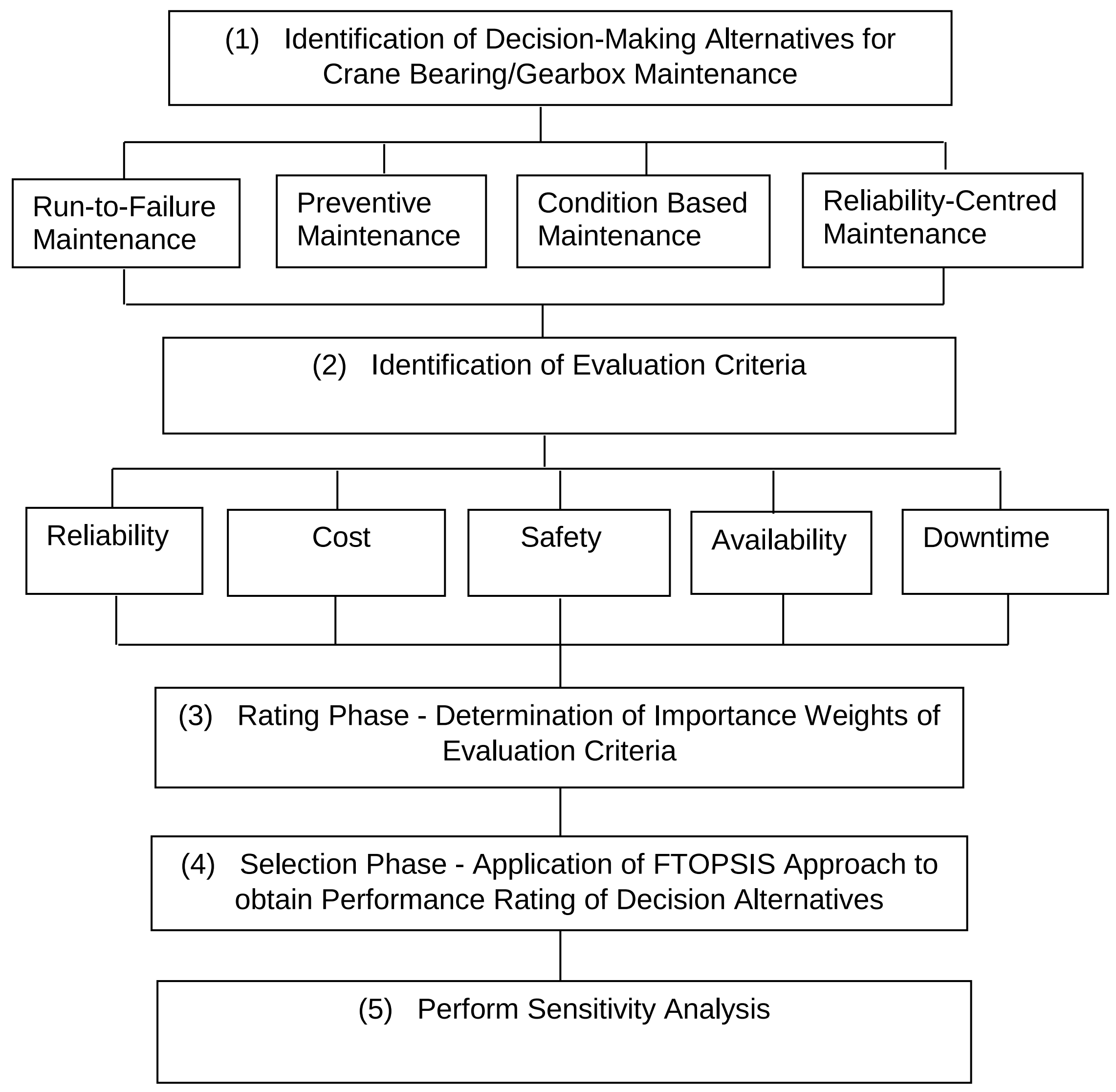


Figure 6.1 Hierarchical Model of Decision Making Analysis for Equipment

A spreadsheet is used to compute the performance ratings of these alternatives. Results of the decision analysis are ranked in their order of preference by the analysts for a final selection and adaptation by the decision-makers (e.g. Maintenance Engineer on-board) or end-users within the marine and offshore industry.

### 6.2.1 Identification of Decision-Making Alternatives (Step one)

The four decision making alternatives (Run-to-failure, preventive maintenance, condition-based maintenance, and reliability centred maintenance) described below have been identified and applied in this model. The maintenance strategies have been selected from the operations and maintenance best practices, as well as the machinery oil analysis, methods, automation, and benefits recommended by Sullivan *et al.* (2010) and Toms and Toms (2008), respectively.

### 6.2.2 Identification of Evaluation Criteria (Step two)

ABB (2016) and Toms and Toms (2008) identify reliability, cost effectiveness, operational safety, availability, and equipment downtime as the main attributes critical to enhancing the selection of an ideal maintenance strategy in an uncertain environment. These five attributes, described below, have been applied in this model as evaluation criteria to reduce the elicitation process and to serve as a check for completeness and transparency.

#### 6.2.2.1 Reliability

The study of component and process reliability is the basis of many efficiency evaluations in operation management (Carlo, 2015). Reliability has long been considered to be one of the three related attributes that must be taken into consideration when making, buying, or using a piece of equipment or component. It describes the ability of a system or component to function under stated conditions for a specified period of time. However, Toms and Toms (2008) identify reliability as the probability that an equipment system will operate at a specified performance level for a specific period. ABS (2016) also perceives reliability as the probability that an item will perform its intended function for a specified interval under stated conditions.

In a broader way, Carlo (2015) identifies reliability as science to predict, analyze, prevent and mitigate failures over time. It is a science, with its theoretical basis and principles. It also has sub-disciplines, all related in some way to the study and knowledge of faults. Reliability also has to do with psychology and psychiatry (Carlo (2015) given that the human element is almost always part of the systems.

#### 6.2.2.2 Cost

This cost includes equipment capital cost, cost due to unplanned downtime of equipment, labour cost, and cost involved with repair or replacement of equipment. An independent study conducted by Forrester Consulting on behalf of ABB Turbocharging reveals that organisations are under pressure to reduce cost, and that the three quarterly reports always consider the cost implications of parts and services (ABB, 2016). History, however, reveals that not all equipment operators utilize maintenance strategy in the most cost effective manner (Taylor, 1995). Decreasing unplanned downtime, and costs of maintenance, availability, and reliability are therefore significant considerations for investing in capital-intensive machinery.

#### 6.2.2.3 Safety

There are numerous definitions of safety among professionals and researchers in the safety and risk fields. For example, Leveson (1995, 2004) cited in Aven (2013) defines safety as "the absence of accidents, where an accident is defined as an event involving an unplanned and unacceptable loss". Safety is also linked to risk and uncertainty as Moller *et al*. (2006) views safety as the opposite of risk, while, Aven (2013) considers epistemological uncertainty of great importance when discussing safety and safety matters, but argues that this uncertainty aspect is not reflected in many perceptions of risk.

Safety can also refer to the control of recognized hazards in order to achieve an acceptable level of risk. Safe operation of marine and offshore equipment is very important, thus, the general safety guidance for equipment is to be adhered to at all times. Potential hazards of operating machines and equipment are numerous, and thus, machine and equipment operators are encouraged to become familiar with the standards for safe machine and equipment operations relevant to their work (Toms and Toms, 2008). With this, it is envisaged that risks associated with the machines / equipment can be reduced to a feasible and acceptable level.

#### 6.2.2.4 Equipment availability

Availability, according to Carlo (2015) may be defined as the percentage of time that a repairable system is in an operating condition. Toms and Toms (2008) view equipment availability as the degree to which the machine / equipment in context is in a specified operable and committable state at the start of operation, when the operation is called for at an unknown (i.e. a random) time. This basically means that the machine / equipment is suitable and ready for use when needed. However, in literature, equipment availability depends on the reliability and maintainability of that equipment, and availability itself therefore, depends on the time between two consecutive failures, and how long it will takes to restore the system. The ability to measure and control costs of equipment deterioration has an obvious direct impact on equipment availability and operational costs (Toms and Toms, 2008).

#### 6.2.2.5 Equipment downtime

A period during which an equipment or machine is not functional or cannot work is referred to as downtime. Downtime can occur due to technical failure, machine adjustment, maintenance, or non-availability of inputs such as materials, labour, and power (ABB, 2016), (Toms and Toms, 2008). An independent study for ABB Turbocharging found that 87 percent of organizations work only or mostly with Original Equipment Manufacturers

(OEMs) for maintenance support and spare parts procurement (ABB, 2016). Key benefits cited were reduced downtime and better parts availability according to the Forrester Consulting Technology Adoption Profile.

### 6.2.3 Rating Phase - Determination of Importance Weights (Step three)

As indicated in the model hierarchy for decision making, the rating phase deals with the determination of importance weights (which includes experts' weights, the criteria's weights with respect to the alternatives), defuzzifying the weights and normalising the decision matrix with respect to the goal. In the next step, the experts allocate linguistic variables to the criteria and the alternatives, respectively. The linguistic terms are calibrated into fuzzy triangular numbers for their fuzzy numbers. Then, FTOPSIS is adopted to aggregate the criteria and the alternative ratings to generate an overall score of the alternatives for ranking.

In fuzzy set theory, conversion scales are applied to transform the linguistic terms into fuzzy numbers for system modelling and analysis. In this study, a conversion scale proposed by Chen and Hwang (1992), is being adopted to rate the evaluation criteria with respect to the decision alternatives. As presented in Figure 6.2, both the performance score $(x)$ and the membership degree $(\mu_x)$ are in the range of 0 and 1.

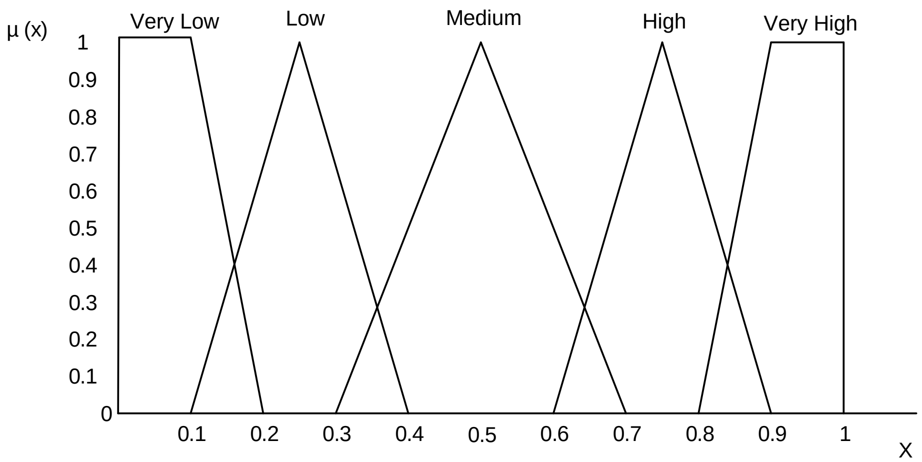


Figure 6.2: Membership Degree for Linguistic Ratings [Chen and Hwang (1992)]

The triangular fuzzy numbers in Figure 6.2 are converted to trapezoidal fuzzy numbers for easy computational analysis in this section, so that information can be represented in a concise and precise manner, as shown in Table 6.1.

At this stage, a series of calculations are conducted on weights of the alternatives and experts used during the collaborative modelling process. To establish a decision matrix for the evaluation process, as shown in Figure 6.2, expert opinions on the decision alternative with respect to each criterion can be made using linguistic variables. Linguistic variables are often used when describing situations that are too complex and fuzzy to be analysed quantitatively (Vahdat *et al.,* 2014a). Human judgements, including preferences, are often vague and their preferences cannot be indicated by an exact numerical value (Vahdat *et al.,* 2014b), therefore, a more realistic approach may be to use linguistic assessments such as “very good”, “medium good” and “good” instead of numerical values.

**Table 6.1:** Fuzzy Linguistic Scale for Alternative Rating

| **Linguistic Variables** | **Corresponding Trapezoidal Fuzzy Numbers** |
|---|---|
| Very Low | (0, 0, 0.1, 0.2) |
| Low | (0.1, 0.25, 0.25, 0.4) |
| Medium | (0.3, 0.5, 0.5, 0.7) |
| High | (0.6, 0.75, 0.75, 0.9) |
| Very High | (0.8, 0.9, 1, 1) |

*Source: Hypothetical data [Chen and Hwang (1992)]*

#### 6.2.3.1 Estimating weights of experts

The weight of the expert can be determined in a simplified manner using established methods such as simple rating methods or more elaborate methods based on the weighting scores and factors. For this study, the weights of the experienced experts used are considered to be equal. Table 6.2 shows the composition and classification of these experts.

**Table 6.2:** Classification of Experts

| **Composition** | **Classification** |
|---|---|
| Industry Position | • Senior Maintenance Engineer<br>• Ship Chief Engineer<br>• Senior Port Maintenance Engineer |
| Service Time | >25 years |
| Academic Qualification | • PhD<br>• Class 1 Certificate of Competency<br>• Master |

*Source: Test case data*

#### 6.2.3.2 Estimating weights of criteria

The weights of criteria have played a vital role in measuring the overall preference values of the alternatives in many MCDM models. Based on the different assumptions on $U(Z(x))$ or $U(R(x))$, MCDM models have different aggregation rules that allow the use of the criteria weights in different ways. Moreover, distinct methods for assessing criteria weights are designed for different aggregation rules (Choo *et al.,* 1999). In this study, the weights of the five criteria proposed are considered to be equal.

#### 6.2.3.3 Aggregation of experts' opinions

Based on the literature review presented in Chapter 2, when carrying out collaborative modelling of large and sophisticated engineering machinery, experts may have different opinions; thus, it is essential to aggregate these opinions in a logical, systematic, and simplified manner. In line with the modelling approach presented in Hsu and Chen (1994), consider that each expert $E_u$ $(u = 1, 2, 3, \ldots M)$ expresses their opinions on a particular criterion based on their expertise by a set of linguistic variables that are described by fuzzy numbers. The aggregation of the experts' judgement can be obtained as follows:

1. Calculate the degree of agreement (degree of similarity) $S_{uv}(\check{\delta}_u \check{\delta}_v)$ of the opinions $\check{\delta}_U$ and $\check{\delta}_v$ of a pair of experts $E_u$ and $E_v$ where $S_{uv}(\check{\delta}_u \check{\delta}_v)$ ∈ (0, 1). Based on this approach, $\check{X}$ = $(a_1, a_2, a_3, a_4)$ and $\check{Y}$ = $(b_1, b_2, b_3, b_4)$ are trapezoidal fuzzy numbers. The degree of similarity between these two fuzzy numbers can be evaluated by the similarity function S defined as follows (Hsu and Chen, 1994):

$$S(\check{X}, \check{Y}) = 1 - \frac{1}{4} \sum_{i=1}^{4} |a_i - b_i| \tag{6.1}$$

where $S(\check{X}, \check{Y})$ ∈ (0, 1). It is important to mention that the larger the value of $S(\check{X}, \check{Y})$, the greater the similarity between two fuzzy numbers of $\check{X}$ and $\check{Y}$ respectively.

2. Calculate the degree of average agreement (AA) of expert $E_u$; this can be obtained using Equation (6.2).

$$AA(E_u) = \frac{1}{N-1} \sum_{\substack{u \neq v \\ v=1}}^{N} S(\check{\delta}_u, \check{\delta}_v) \tag{6.2}$$

3. Calculate the relative agreement (RA) degree $RA(E_u)$ of experts $E_u$; this can be obtained as follows:

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{N} AA(E_u)} \tag{6.3}$$

4. Calculate the consensus coefficient degree $CC$ of experts $E_u$ $(u = 1, 2, \ldots M)$; this can be analysed as follows:

$$CC(E_u) = \beta . w(E_u) + (1 - \beta) . RA(E_u) \tag{6.4}$$

where $\beta (0 \leq \beta \leq 1)$ is a relaxation factor of the proposed approach. It highlights the important of $w(E_u)$ over $RA(E_u)$. It is important to note that when $\beta = 0$, no importance has been given to the weight of experts and, thus, a homogeneous group of experts is used. When $\beta = 1$, then the consensus degree of an expert is the same as its importance weight.

The consensus coefficient degree of each expert is a good measure for evaluating the relative worthiness of judgement of all experts participating in the decision making process. John *et al*., (2014) believe that it is the responsibility of the decision maker to assign an appropriate value of $\beta$, and considered $\beta$ to be 0.75.

5. The expert aggregation judgement $\check{R}_{AG}$ can be obtained as follows:

$$\check{R}_{AG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 + \cdots + \cdots CC(E_m) \times \tilde{R}_n \quad (6.5)$$

where $\tilde{R}_i (i = 1, 2, \dots n)$ is the subjective rating of a given criterion with respect to alternative by expert $E_u(u = 1, 2, \dots m)$.

#### 6.2.3.4 Defuzzification of the aggregated fuzzy results

In order to rank the alternatives of the decision problem, all aggregated fuzzy numbers must be defuzzified. Each element of matrix $\tilde{x}_i = (a_1, a_2, a_3, a_4)$ can be converted to a crisp value using Equation 6.3 proposed by Sugeno (1999) using the centre of area defuzzification technique. Equation 6.3 is adapted within this study because of the ease in the computation process compared to other techniques in the literature, such as Chen (2000).

$$X^* = \frac{\int_{a_1}^{a_2} \frac{x-a}{a_2-a_1} x dx + \int_{a_2}^{a_3} x dx + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} x dx}{\int_{a_1}^{a_2} \frac{x-a}{a_2-a_1} dx + \int_{a_2}^{a_3} dx + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} dx} = \frac{1}{3} \frac{(a_4+a_3)^2 - a_4 a_3 - (a_1+a_2)^2 + a_1 a_2}{a_4+a_3-a_1-a_2} \quad (6.6)$$

### 6.2.4 Selection Phase - Application of FTOPSIS Approach to Obtain Performance Rating of Decision Alternatives (Step four)

Selection of best maintenance strategies often requires analysts to provide both quantitative and qualitative assessments for determining the performance of each alternative with respect to each criterion. A modelling approach that will handle uncertain, imprecise, indefinite, and subjective data that often result from such assessments in a flexible manner is required. As a consequence of that, this study utilises a FTOPSIS algorithm (Yang *et al*., 2009), (Jahanshahloo *et al*., 2006), and (Chen, 2000) due to the fact that fuzzy sets might provide the needed flexibility to represent the vague information resulting from the lack of data or knowledge. TOPSIS can reasonably deal with the multiplicity of the criteria in order to rank the alternatives based on the aggregated decision matrix and weight vector analysis. To carry out the assessment, consider $x$ possible alternatives $A_1, A_2, A_3 \dots A_x$ from which $E_u$ decision-makers $E_u = (1, 2, 3, \dots m)$ have to make a credible decision on an appropriate maintenance strategy on the basis of $n$ sets of criteria $C_1, C_2, C_3, \dots C_n$. The decision support procedure is achieved through the following steps:

#### 6.2.4.1 Fuzzy decision matrix construction

This step involves choosing appropriate linguistic variables for the alternatives with respect to criteria. Suppose the aggregation rate of alternative $A_1(i = 1, 2, \dots x)$ for criteria $C_1(j = 1, 2, \dots n)$ is $(t_{ij})$. Therefore, TOPSIS can be expressed in a matrix format as follows:

$$Z = (t_{ij})_{y \times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ t_{x1} & t_{x2} & \cdots & t_{xn} \end{bmatrix} \end{array} \quad i = 1, 2, \dots., x; \;\; j = 1, 2, \dots., n \qquad (6.7)$$

where, matrix $Z$ is composed of $x$ alternatives and $n$ criteria.

In the proposed model, the process for the estimation of the values for the best maintenance strategy for marine and offshore machinery will depend on expert knowledge and judgement of the decision analysts.

#### 6.2.4.2 Fuzzy decision matrix normalisation

After producing the decision matrix for the alternatives, the fuzzy data obtained in the matrix are normalised in order to eliminate the units of criteria scores, so that numerical comparisons often associated with MCDM problems can be brought to the same perception. The process involves dividing the score within each criterion by the root-sum-of-squares for all the decision-making criteria. Normalisation has two main aims:

1. For the comparison of heterogeneous criteria.
2. To ensure that all triangular fuzzy numbers are ranged within the interval, 0 and 1 (Wang and Chang, 2007).

Since $n$ criteria may be measured in different ways, the decision matrix $Z$ needs to be normalised. This step transforms various criteria dimensions into non-dimensional units, which allows for comparisons across the criteria. The normalised decision matrix can be obtained by using the matrix given in 6.8.

$$R = (r_{ij})_{y \times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{x1} & r_{x2} & \cdots & r_{xn} \end{bmatrix} \end{array} \qquad (6.8)$$

#### 6.2.4.3 Construction of weighted normalisation fuzzy decision matrix

The weighting factors are a set of percentages that add up to 100%, with the most important alternative receiving the highest weighting factor. The process involves multiplying the importance weights of the alternative by the values in the normalised fuzzy decision matrix. Considering the different importance of each criterion, the weighted normalized fuzzy-decision matrix $\tilde{V}$ can be constructed using Equations 6.9 and 6.10.

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{mxn}, \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n \tag{6.9}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij}\ x\ \widetilde{w}_j \tag{6.10}$$

where, $\widetilde{w}_j$ denotes the importance weight of criterion $C_j$.

#### 6.2.4.4 Determination of the fuzzy positive ideal reference point (FPIRP) and fuzzy negative ideal reference point (FNIRP)

The FPIRP is obtained by identifying the best score in a criterion. Similarly, the worst score of a criterion is identified and recorded as the FNIRP. The FPIRP ($A^+$) [the benefit criterion] and FNIRP ($A^-$) [the cost criterion) are defined as follows:

$$A^+ = (v_1^+, v_2^+, \dots, v_n^+), \tag{6.11}$$

$$A^- = (v_1^-, v_2^-, \dots, v_n^-), \tag{6.12}$$

where,

$$\tilde{v}_j^+ = \left\{Max\ v_{ij}, i\ \in\ j_1; Min\ v_{ij}, i\ \in j_2\right\} \tag{6.13}$$

$$\tilde{v}_j^- = \left\{Max\ v_{ij}, i\ \in\ j_1; Min\ v_{ij}, i\ \in j_2\right\} \tag{6.14}$$

where $j_1$ and $j_2$ are associated with the sets of benefit and cost criteria respectively.

The distance of each alternative (maintenance strategy) from the FPIRP ($D_i^+$) and FNIRP ($D_i^-$) with respect to each criterion can be obtained by utilising Equations 6.15 and 6.16 respectively.

$$D_i^+ = \sqrt{\textstyle\sum_{i=1}^{x}(v_{ij} - v_i^+)^2}, \quad j - 1, 2, \dots, n \tag{6.15}$$

$$D_i^- = \sqrt{\textstyle\sum_{i=1}^{x}(v_{ij} - v_i^-)^2}, \quad j - 1, 2, \dots, n \tag{6.16}$$

The obtained $D_i^+$ and $D_i^-$ values can then be used in obtaining the Closeness Coefficient ($CC_i$) of each alternative for ranking purposes.

#### 6.2.4.5 Obtaining the closeness coefficient of each alternative

The ranking of the alternative can be determined after the obtaining $CC_i$. This allows the decision making experts to choose the most rational and appropriate alternative. To calculate the $CC_i$ Equation 6.17 is used.

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad i = 1, 2, \dots, m \tag{6.17}$$

#### 6.2.4.6 Ranking the alternatives

The different alternatives are ranked according to the closeness coefficient $CC_i$ in decreasing order. It is important to note that the best alternative is closest to the FPIRP and farthest from the FNIRP. This means that the larger the $CC_i$, the better the associated alternative.

### 6.2.5 Perform Sensitivity Analysis (Final)

Conducting a sensitivity analysis (SA) is an important aspect of the novel hybrid methodology presented in Section 6.2, as it is meant to provide a reasonable amount of confidence in the overall result of the study. Given that the final output result is dependent on the subjective judgements of the decision makers, it is essential to perform SA based on a set of scenarios that reflect different views on the relative importance of the attributes, in order to observe the stability and ranking order of the model's output. Then, managerial attention is focused during implementation of the maintenance strategies for the decision making process.

## 6.3 Application of Methodology to a Test Scenario

The proposed model will be demonstrated in a decision making analysis of the selection of an on-board machinery (crane) maintenance strategy for ships operating under an uncertain environment, as presented in Section 6.2. The hierarchical model of this decision-making analysis process is as illustrated in Figure 6.3, with the goal of the decision problem in level 0, decision alternatives in level 1, and evaluation criteria in level 2. It is important to note that the proposed model is applied for decision making in the selection of appropriate maintenance strategies for marine and offshore machinery.

This representation is made to simplify the computational complexity associated with the analysis and to provide managerial insight to decision makers in a reasonable manner prior to their subjective evaluation of criteria with respect to alternatives. The analysis will be conducted through a robust literature review and brainstorming session with the experts. The positions of the experts and their degree of competency in the industry are as shown in Table 6.7. The primary objective of the decision-making analysis is to identify the best, most appropriate and acceptable maintenance strategy to be adopted by the engineer on-board ships and offshore installations.

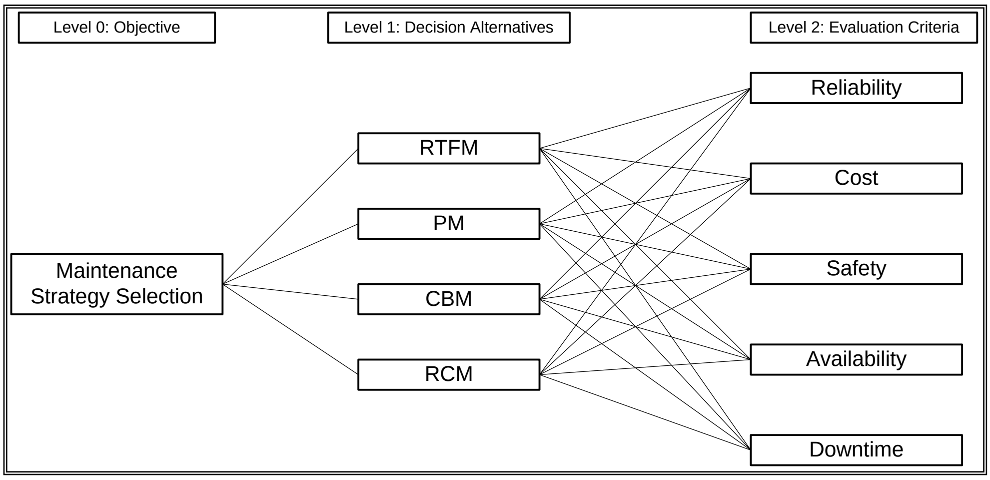


Figure 6.3: Hierarchical Structure of Maintenance Strategy Selection

***Note:*** *RTFM, PM, CBM, and RCM stand for Run-to-Failure Maintenance, Preventive Maintenance, Condition Based Maintenance, and Reliability Centred Maintenance, respectively*.

### 6.3.1 Identification of Decision Making Alternatives (Step one)

This involves the identification of the decision making alternatives through a literature review of the machinery maintenance strategies on-board ships. As presented in section 6.2.1, four (4) alternatives were established for this analysis.

### 6.3.2 Identification of Evaluation of Criteria (Step two)

Based on the expert opinions, the criteria or attributes that are critical to enhancing the selection of the best maintenance strategy in uncertain situations are stated in section 6.2.2. It is evident that the criteria used for the selection procedure consist of two main categories: cost (C) (the lower the value, the more effective the alternative) and benefit (B) (the higher the value, the more robust or effective the alternative). As a consequence, the cost type criteria include the cost (equipment capital cost, labour cost, repair/replacement cost), downtime, and availability, while the benefit type criteria consist of safety (operational safety, environmental safety) and reliability. The assigned criteria are described in Table 6.3. Based on this, it is worth mentioning that maintenance strategy selection can be carried out with respect to three cost and two benefit criteria.

**Table 6.3:** Criteria for Maintenance Strategy Selection

| Criteria | Criteria Description | Assessment Type | Category |
|---|---|---|---|
| C1 | Reliability | Linguistic Assessment | B |
| C2 | Cost | Linguistic Assessment | C |
| C3 | Safety | Linguistic Assessment | B |
| C4 | Availability | Linguistic Assessment | C |
| C5 | Downtime | Linguistic Assessment | C |

*Source: Test case data*

### 6.3.3 Rating Phase - Determination of Importance Weight (Step three)

In order to show the relative important of each criterion, it is necessary to assign a weight to each (Reliability, Cost Effectiveness, Safety, Availability, and Downtime). There are two types of criteria for a selection problem involving complex networks of decision making. If an assessment of the criteria is made with respect to alternatives from field data or a literature review, the criteria are called ‘objective’; when such information is obtained using expert judgement in the form of fuzzy linguistic estimates, then the criteria are called ‘subjective’. The assessment type used for all the criteria in this model is fuzzy linguistic estimates, thus, the criteria are subjective. Based on this, each subjective criterion is assessed with respect to each alternative by a group of three experts or decision makers (DMs), and their assessments are presented in Tables 6.4, 6.5, and 6.6, respectively. The experts’ backgrounds are presented as follows:

1. A senior maintenance engineer with a PhD who has been involved with marine and offshore machinery maintenance and services for over 25 years.
2. A ship chief engineer officer with a class 1 marine certificate of competency (COC) who has been involved with machinery maintenance and operations on-board ship for over 25 years.
3. A senior port maintenance engineer with a master’s degree who has been involved with the port equipment’s safety and operational services for over 30 years.

**Table 6.4:** Linguistic Assessment of the Alternatives with Respect to Criteria by Expert 1

| | EXPERT 1 | | | |
|---|---|---|---|---|
| | **RTFM** | **PM** | **CBM** | **RCM** |
| Reliability | H | H | VH | VH |
| Cost | L | VH | M | VL |
| Safety | L | VH | M | VL |
| Availability | M | VH | VH | VH |
| Downtime | H | L | VL | VL |

*Source: Test case data*

**Table 6.5:** Linguistic Assessment of the Alternatives with Respect to Criteria by Expert 2

| | EXPERT 2 | | | |
|---|---|---|---|---|
| | **RTFM** | **PM** | **CBM** | **RCM** |
| Reliability | H | H | VH | VH |
| Cost | VL | H | L | VL |
| Safety | L | VH | M | VL |
| Availability | M | H | VH | VH |
| Downtime | H | VL | VL | VL |

*Source: Test case data*

**Table 6.6:** Linguistic Assessment of the Alternatives with Respect to Criteria by Expert 3

| | EXPERT 3 | | | |
|---|---|---|---|---|
| | **RTFM** | **PM** | **CBM** | **RCM** |
| Reliability | M | H | VH | VH |
| Cost | L | H | M | L |
| Safety | L | H | M | VL |
| Availability | M | M | VH | H |
| Downtime | M | VL | VL | L |

*Source: Test case data*

***Note:*** *VL, L, M, H and VH stand for Very Low, Low, Medium, High, and Very High, respectively.*

#### 6.3.3.1 Estimating weights of experts

The weights of the experts are determined based on the available information in Section 6.2.3.1. The industrial positions, service times, and academic qualifications of the experts or decision-makers are extracted from Table 6.2 and utilised. As shown in Table 6.7, the weights of these three experts are considered to be equal and this is indicated as degree of competency (0.333).

**Table 6.7:** Selected Experts and their Assigned Degree of Competency

| **Decision Makers** | **Industrial Position** | **Service Period** | **Academic Qualification** | **Degree of Competency** |
|---|---|---|---|---|
| DM1 | Senior Maintenance Engineer | >25 years | PhD | 0.333 |
| DM2 | Ship Chief Engineer | >25 years | Class 1 Certificate of Competency | 0.333 |
| DM3 | Senior Port Maintenance Engineer | >25 years | Master | 0.333 |

*Source: Test case data*

#### 6.3.3.2 Estimating weights of criteria

For this model, equal weight values are assigned to the five identified evaluation criteria, as shown in Table 6.8. These weight values will then be applied in the assessment process to establish the fuzzy performance ratings of the model's evaluation alternatives.

**Table 6.8:** Weights of Criteria

| Criteria | Assigned Weights |
|---|---|
| Reliability | 0.2 |
| Cost | 0.2 |
| Safety | 0.2 |
| Availability | 0.2 |
| Downtime | 0.2 |

*Source: Test case data*

#### 6.3.3.3 Aggregation of experts' opinions

This stage of the analysis involves a series of aggregation calculations of criteria ratings with respect to alternatives. Since decision making on maintenance strategies involves complex networks of group decision making in a fuzzy environment, it is important to emphasise that three experts are employed for this strategic evaluation; for this study, their weights are considered to be equal. When conducting the Fuzzy-TOPSIS process as applied in this model, the knowledge and judgement of analysts involved are to be considered. The four decision alternatives and five evaluation criteria shown in Table 6.9 will be used to develop the fuzzy TOPSIS decision matrix.

Tables 6.10, 6.11, and 6.12 show the corresponding fuzzy numbers of the alternatives with respect to the criteria by the three experts. The figures obtained are based on the membership functions of the linguistic variables developed in Figure 6.2 and the scale for the measurement of the evaluation criteria, as shown in Table 6.1.

Aggregation calculations are conducted using Equations 6.1, 6.2, 6.3, 6.4, and 6.5 for the experts' judgement on reliability with respect to run-to-failure maintenance, as seen in Table 6.13. Similar, calculations were conducted on the other attributes and their fuzzy estimates are presented in Tables 6.14a and 6.14b.

**Table 6.9:** Decision Alternatives and Evaluation Criteria

| | Decision Alternatives | | Evaluation Criteria |
|---|---|---|---|
| A1 | Run-to-Failure Maintenance | C1 | Reliability |
| A2 | Preventive Maintenance | C2 | Cost |
| A3 | Condition Based Maintenance | C3 | Safety |
| A4 | Reliability-Centred Maintenance | C4 | Availability |
| | | C5 | Downtime |

*Source: Test case data*

**Table 6.10:** Fuzzy Numbers for Alternatives with Respect to Criteria by Expert 1

| | Expert 1 | | | |
|---|---|---|---|---|
| | **A1** | **A2** | **A3** | **A4** |
| **C1** | 0.6, 0.75, 0.75, 0.9 | 0.6, 0.75, 0.75, 0.9 | 0.8, 0.9, 1, 1 | 0.8, 0.9, 1, 1 |
| **C2** | 0.1, 0.25, 0.25, 0.4 | 0.8, 0.9, 1, 1 | 0.3, 0.5, 0.5, 0.7 | 0, 0, 0.1, 0.2 |
| **C3** | 0.1, 0.25, 0.25, 0.4 | 0.8, 0.9, 1, 1 | 0.3, 0.5, 0.5, 0.7 | 0, 0, 0.1, 0.2 |
| **C4** | 0.3, 0.5, 0.5, 0.7 | 0.8, 0.9, 1, 1 | 0.8, 0.9, 1, 1 | 0.8, 0.9, 1, 1 |
| **C5** | 0.6, 0.75, 0.75, 0.9 | 0.1, 0.25, 0.25, 0.4 | 0, 0, 0.1, 0.2 | 0, 0, 0.1, 0.2 |

*Source: Test case data*

**Table 6.11:** Fuzzy Numbers for Alternatives with Respect to Criteria by Expert 2

| | Expert 2 | | | |
|---|---|---|---|---|
| | **A1** | **A2** | **A3** | **A4** |
| **C1** | 0.6, 0.75, 0.75, 0.9 | 0.6, 0.75, 0.75, 0.9 | 0.8, 0.9, 1, 1 | 0.8, 0.9, 1, 1 |
| **C2** | 0, 0, 0.1, 0.2 | 0.6, 0.75, 0.75, 0.9 | 0.1, 0.25, 0.25, 0.4 | 0, 0, 0.1, 0.2 |
| **C3** | 0.1, 0.25, 0.25, 0.4 | 0.8, 0.9, 1, 1 | 0.3, 0.5, 0.5, 0.7 | 0, 0, 0.1, 0.2 |
| **C4** | 0.3, 0.5, 0.5, 0.7 | 0.6, 0.75, 0.75, 0.9 | 0.8, 0.9, 1, 1 | 0.8, 0.9, 1, 1 |
| **C5** | 0.6, 0.75, 0.75, 0.9 | 0, 0, 0.1, 0.2 | 0, 0, 0.1, 0.2 | 0, 0, 0.1, 0.2 |

*Source: Test case data*

**Table 6.12:** Fuzzy Numbers for Alternatives with Respect to Criteria by Expert 3

| | Expert 3 | | | |
|---|---|---|---|---|
| | **A1** | **A2** | **A3** | **A4** |
| **C1** | 0.3, 0.5, 0.5, 0.7 | 0.6, 0.75, 0.75, 0.9 | 0.8, 0.9, 1, 1 | 0.8, 0.9, 1, 1 |
| **C2** | 0.1, 0.25, 0.25, 0.4 | 0.6, 0.75, 0.75, 0.9 | 0.3, 0.5, 0.5, 0.7 | 0.1, 0.25, 0.25, 0.4 |
| **C3** | 0.1, 0.25, 0.25, 0.4 | 0.6, 0.75, 0.75, 0.9 | 0.3, 0.5, 0.5, 0.7 | 0, 0, 0.1, 0.2 |
| **C4** | 0.3, 0.5, 0.5, 0.7 | 0.3, 0.5, 0.5, 0.7 | 0.8, 0.9, 1, 1 | 0.6, 0.75, 0.75, 0.9 |
| **C5** | 0.3, 0.5, 0.5, 0.7 | 0, 0, 0.1, 0.2 | 0, 0, 0.1, 0.2 | 0.1, 0.25, 0.25, 0.4 |

*Source: Test case data*

**Table 6.13:** Aggregation Calculation for Reliability with Respect to RTFM

| | | |
|---|---|---|
| Expert 1 | H | 0.6, 0.75, 0.75, 0.9 |
| Expert 2 | H | 0.6, 0.75, 0.75, 0.9 |
| Expert 3 | M | 0.3, 0.5, 0.5, 0.7 |
| S(Expert 1 & 2) = 1 - $\frac{(0.6-0.6)+(0.75-0.75)+(0.75-0.75)+(0.9-0.9)}{4} = 1$ | | |
| S(Expert 1 & 3) = 1 - $\frac{(0.6-0.3)+(0.75-0.5)+(0.75-0.5)+(0.9-0.7)}{4} = 0.75$ | | |
| S(Expert 2 & 3) = 1 - $\frac{(0.6-0.3)+(0.75-0.5)+(0.75-0.5)+(0.9-0.7)}{4} = 0.75$ | | |
| AA(Expert 1) = $\frac{1+0.75}{2} = 0.875$ | AA(Expert 2) = $\frac{1+0.75}{2} = 0.875$ | AA(Expert 3) = $\frac{0.75+0.75}{2} =$ $0.75$ |
| RA(Expert1) = $\frac{0.875}{0.875+0.875+0.75} = 0.35$ | RA(Expert2) = $\frac{0.875}{0.875+0.875+0.75} = 0.35$ | RA(Expert3) = $\frac{0.75}{0.875+0.875+0.75} = 0.3$ |
| Expert aggregation Result $\tilde{R}_{AG}$ | 0.35(0.6, 0.75, 0.75, 0.9) + 0.35(0.6, 0.75, 0.75, 0.9) + 0.3(0.3, 0.5, 0.5, 0.7) = (0.51, 0.675, 0.675, 0.84) | |

*Source: Test case data*

**Table 6.14a**: Aggregation Results of Criteria Ratings with Respect to Alternatives

| | C1 | C2 | C3 |
|---|---|---|---|
| **A1** | 0.51, 0.675, 0.675, 0.84 | 0.067, 0.167, 0.2, 0.333 | 0.1, 0.25, 0.25, 0.4 |
| **A2** | 0.6, 0.75, 0.75, 0.9 | 0.662, 0.797, 0.828, 0.931 | 0.738, 0.853, 0.922, 0.969 |
| **A3** | 0.8, 0.9, 1, 1 | 0.233, 0.417, 0.417, 0.6 | 0.3, 0.5, 0.5, 0.7 |
| **A4** | 0.8, 0.9, 1, 1 | 0.035, 0.088, 0.153, 0.270 | 0, 0, 0.1, 0.2 |

*Source: Test case data*

**Table 6.14b**: Aggregation Results of Criteria Ratings with Respect to Alternatives

| | C4 | C5 |
|---|---|---|
| **A1** | 0.3, 0.5, 0.5, 0.7 | 0.51, 0.675, 0.675, 0.84 |
| **A2** | 0.573, 0.722, 0.754, 0.871 | 0.031, 0.078, 0.147, 0.262 |
| **A3** | 0.8, 0.9, 1, 1 | 0, 0, 0.1, 0.2 |
| **A4** | 0.738, 0.853, 0.922, 0.969 | 0.035, 0.088, 0.153, 0.270 |

*Source: Test case data*

6.3.3.4 Defuzzification of the aggregated fuzzy results

Based on the aggregation results presented in Tables 6.14a and 6.14b, the fuzzy numbers are converted into crisp values using Equation 6.6 and the results are presented in Table 6.15.

**Table 6.15:** Transformation of the Fuzzy Numbers into Crisp Values

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| **A1** | (0.51+ 0.675 + 0.675 + 0.84) / 4 = 0.675 | (0.067 + 0.167 + 0.2 + 0.333) / 4 = 0.192 | (0.1 + 0.25 + 0.25 + 0.4) / 4 = 0.25 | (0.3 + 0.5 + 0.5 + 0.7) / 4 = 0.5 | (0.51+ 0.675 + 0.675 + 0.84) / 4 = 0.675 |
| **A2** | (0.6 + 0.75 + 0.75 + 0.9) / 4 = 0.75 | (0.662 + 0.797 + 0.828 + 0.931) / 4 = 0.805 | (0.738 + 0.853 + 0.922 + 0.969) / 4 = 0.871 | (0.573 + 0.722 + 0.754 + 0.871) / 4 = 0.730 | (0.031 + 0.078 + 0.147 + 0.262) / 4 = 0.130 |
| **A3** | (0.8 + 0.9 + 1 + 1) / 4 = 0.925 | (0.233 + 0.417 + 0.417 + 0.6) / 4 = 0.417 | (0.3 + 0.5 + 0.5 + 0.7) / 4 = 0.5 | (0.8 + 0.9 + 1 + 1) / 4 = 0.925 | (0 + 0 + 0.1 + 0.2) / 4 = 0.075 |
| **A4** | (0.8 + 0.9 + 1 + 1) / 4 = 0.925 | (0.035 + 0.088 + 0.153 + 0.270) / 4 = 0.136 | (0 + 0 + 0.1 + 0.2) / 4 = 0.075 | (0.738 + 0.853 + 0.922 + 0.969) / 4 = 0.871 | (0.035 + 0.088 + 0.153 + 0.270) / 4 = 0.136 |

*Source: Test case data*

6.3.4 Selection Phase - Application of FTOPSIS Approach to Obtain Performance Rating of Decision Alternatives (Step four)

In order to obtain the performance rating for the decision alternatives, the FTOPSIS algorithm is applied in this section, as follows:

#### 6.3.4.1 FTOPSIS decision matrix construction

Based on crisp values obtained for the four decision-making alternatives (A1 – A4) and five evaluation criteria (C1 – C5) obtained in Table 6.15, a Fuzzy-TOPSIS decision matrix, shown in Tables 6.16, is constructed.

**Table 6.16:** Fuzzy-TOPSIS Decision Matrix

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| **A1** | 0.675 | 0.192 | 0.25 | 0.5 | 0.675 |
| **A2** | 0.75 | 0.805 | 0.871 | 0.730 | 0.130 |
| **A3** | 0.925 | 0.417 | 0.5 | 0.925 | 0.075 |
| **A4** | 0.925 | 0.136 | 0.075 | 0.871 | 0.136 |

*Source: Test case data*

#### 6.3.4.2 Fuzzy decision matrix normalisation

Based on Equation 2.26, the fuzzy decision matrix presented in Table 6.16 is normalised. The results are presented in Table 6.17.

As an example, the normalised reliability (C1) with respect run-to-failure maintenance (A1) is presented as follows:

$$\frac{0.675}{[(0.675^2+0.75^2+0.925^2+0.925^2)]^{\frac{1}{2}}} = 0.409$$

**Table 6.17:** Normalised Decision Matrix

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| **A1** | 0.409 | 0.205 | 0.241 | 0.323 | 0.958 |
| **A2** | 0.454 | 0.859 | 0.839 | 0.471 | 0.184 |
| **A3** | 0.560 | 0.445 | 0.482 | 0.597 | 0.106 |
| **A4** | 0.560 | 0.145 | 0.072 | 0.563 | 0.193 |

*Source: Test case data*

#### 6.3.4.3 Construction of weighted normalisation fuzzy decision matrix

The weighted normalized decision matrix is achieved by applying Equation 6.9. The normalized fuzzy numbers obtained in Table 6.17 are multiplied by the important weight values of the evaluation criteria given in Table 6.8.

For example, the weighted normalized fuzzy number for A1 of C1 is given as follows:

$v_{1,1}$ = 0.409 x 0.2 = 0.082

Similarly, the weighted normalized fuzzy numbers for other alternatives are calculated and presented in Table 6.18.

**Table 6.18:** Weighted Normalized Decision Matrix

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| **A1** | 0.082 | 0.041 | 0.048 | 0.065 | 0.192 |
| **A2** | 0.091 | 0.172 | 0.168 | 0.094 | 0.037 |
| **A3** | 0.112 | 0.089 | 0.096 | 0.119 | 0.021 |
| **A4** | 0.112 | 0.029 | 0.014 | 0.113 | 0.039 |

*Source: Test case data*

6.3.4.4 Determination of the fuzzy positive ideal reference point (FPIRP) and fuzzy negative ideal reference point (FNIRP)

Determination of the FPIRP can be made by taking the largest element of each benefit criterion and the smallest element of each cost criterion. Ultimately, FNIRP is the reverse of the FPIRP in relation to this representation, as presented in Table 6.19. The distances of each maintenance strategy from FPIRP and FNIRP values with respect to each criterion are calculated using Equations 6.13 and 6.14.

As an example, the distance of alternative A1 to $A^{+}$ is calculated as follows:

$$D^{+} = [(0.112-0.082)^2 + (0.029-0.041)^2 + (0.168-0.048)^2 + (0.065-0.065)^2 + (0.021-0.192)^2]^{1/2} = 0.211$$

$$D^{-} = [(0.082-0.082)^2 + (0.172-0.041)^2 + (0.014-0.048)^2 + (0.119-0.065)^2 + (0.192-0.192)^2]^{1/2} = 0.146$$

Similarly, and by applying Equations 6.13 and 6.14, the distances of other decision alternatives to FPIRP and FNIRP were determined and the results are presented in Table 6.20.

**Table 6.19:** Representation of FPIRP and FNIRP Values

| | Positive Ideal Solution | Negative Ideal Solution |
|---|---|---|
| Reliability (C1) | 0.112 | 0.082 |
| Cost (C2) | 0.029 | 0.172 |
| Safety (C3) | 0.168 | 0.014 |
| Availability (C4) | 0.065 | 0.119 |
| Downtime (C5) | 0.021 | 0.192 |

*Source: Test case data*

**Table 6.20:** Distance of each Alternative to the FPIRP and FNIRP

| | A1 | A2 | A3 | A4 |
|---|---|---|---|---|
| $D^{+}$ | 0.211 | 0.148 | 0.108 | 0.162 |
| $D^{-}$ | 0.146 | 0.220 | 0.209 | 0.212 |

*Source: Test case data*

#### 6.3.4.5 Obtaining the closeness coefficient and ranking of alternatives

Based on the results obtained in Section 6.3.4.4, the closeness coefficient of each alternative can be calculated using Equation 6.17. The calculation of the CC value for alternative A1 is described as follows:

$D_1^+ = 0.211$, and $D_1^- = 0.146$

$CC_1 = \frac{0.146}{0.211+0.146} = 0.408$

Similarly, the CC values for alternatives A2 to A4 can be calculated and the results are presented in Table 6.21.

**Table 6.21:** CC Results and Ranking Order of the Maintenance Strategies

| | **A1** | **A2** | **A3** | **A4** |
|---|---|---|---|---|
| CC | 0.408 | 0.597 | 0.659 | 0.566 |
| Ranking | 4 | 2 | 1 | 3 |

*Source: Test case data*

It can be observed in Table 6.21 that each instance of the hybrid approach produces different values for each maintenance strategy that correspond to the strategic decisions of experts. Obviously, the result of the calculations revealed that A3 and A2 scored the highest CC values compared to the remaining alternatives or strategies. The detailed results of the fuzzy TOPSIS analysis are presented in Table 6.22.

**Table 6.22:** Results of Fuzzy TOPSIS Analysis

| | **Decision-Making Attributes** | $D^+$ | $D^-$ | **CC Values** | **Ranking** |
|---|---|---|---|---|---|
| A1 | Run-to-Failure Maintenance | 0.211 | 0.146 | 0.408 | 4 |
| A2 | Preventive Maintenance | 0.148 | 0.220 | 0.597 | 2 |
| A3 | Condition Based Maintenance | 0.108 | 0.209 | 0.659 | 1 |
| A4 | Reliability-Centred Maintenance | 0.162 | 0.212 | 0.566 | 3 |

*Source: Test case data*

#### 6.3.4.6 Ranking the alternatives

Based on the evaluation of closeness coefficient above, by comparing the values of the four alternatives, as shown in Table 6.22, the ranking order of the maintenance strategies is given as A3 > A2 > A4 > A1. Additionally, Figure 6.4 is obtained based on the analysis result presented in Table 6.22. The graph depicts the sensitivity of the analytical result as being non-linear. It is noteworthy that the procedure outlined in the proposed framework revealed that A3 and A2 seem reasonable and appropriate choices for investment in the ship crane under investigation, in order to improve the performance of the crane’s operations. These maintenance strategies have closeness coefficient values of 0.659 and 0.597 respectively.

### 6.3.5 Perform Sensitivity Analysis (Final)

In order to validate and test the robustness of this model, a sensitivity analysis is conducted. The analysis is necessary in order to test the suitability and sensitivity of the model for decision analysis of the maintenance strategies (as decision alternatives), and for the interpretation and communication of results based on a sensitivity study so that managerial insight can correctly provide guidance for investment in maintenance strategies. Based on the input data presented in Section 6.3.4.1 (Table 6.16), the crisp values of each attribute are slightly varied while the resulting change and the final ranking of the alternatives are observed. This process of analysis is useful in situations of high uncertainties concerned with many factors that need to be modelled when investing in machinery maintenance strategies. Apparently, due to the vagueness surrounding the strategic decision making process, it is usually very challenging to predict and analyse the delivery of the analytical result in a fuzzy environment.

The analysis is conducted under five conditions, as tabulated in Table 6.23. The first step in the sensitivity analysis process involves an increment of the cost values (i.e. C2, C4 and C5) of each decision alternative by 10% and decreasing the benefit values (i.e. C1 and C3) by the same 10%. The next step is to determine the distance of each alternative to FPIRP and FNIRP, then obtain the CC values and observe the results of the final ranking, as described in Sections 6.3.4.4 and 6.3.4.5.

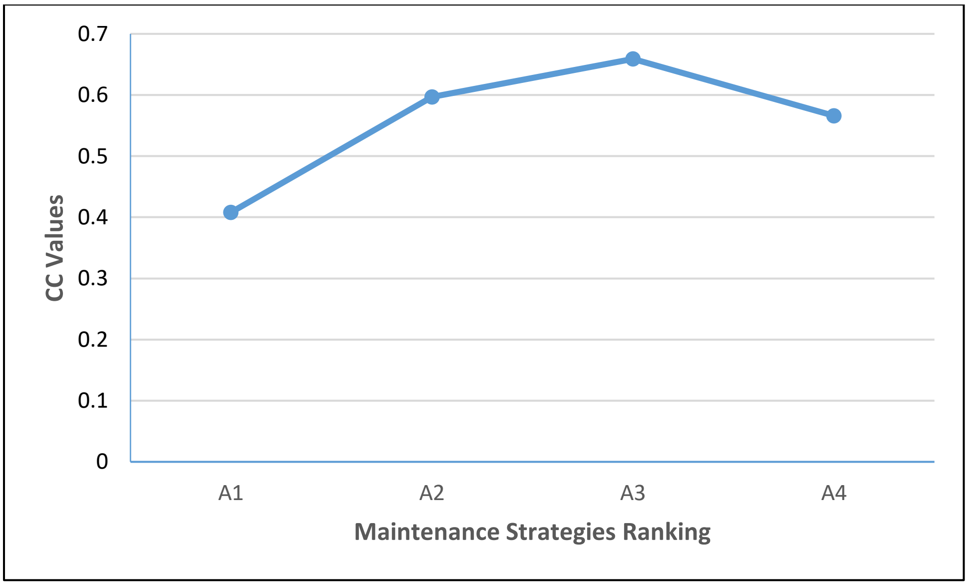


Figure 6.4: Ranking Order of the Maintenance Strategies

Based on Table 6.16 in Section 6.3.4.1, the values for 10% increment on the cost and 10% decrement on the benefit criteria are shown in Table 6.24, and their normalised and weighted normalised values are shown in Tables 6.25 and 6.26, respectively.

**Table 6.23:** Conditions for Changing Input Values by Percentages

| Condition | Percentage |
|---|---|
| 1 | Decrease C1 by 10% |
| 2 | Increase C2 by 10% |
| 3 | Decrease C3 by 10% |
| 4 | Increase C4 by 10% |
| 5 | Increase C5 by 10% |

*Source: Test case data*

**Table 6.24:** Fuzzy-TOPSIS Decision Matrix when Criteria are changed by 10%

| | 10% Decrement | 10% Increment | 10% Decrement | 10% Increment | 10% Increment |
|---|---|---|---|---|---|
| | **C1** | **C2** | **C3** | **C4** | **C5** |
| **A1** | 0.575 | 0.292 | 0.15 | 0.6 | 0.775 |
| **A2** | 0.65 | 0.905 | 0.771 | 0.83 | 0.23 |
| **A3** | 0.825 | 0.517 | 0.4 | 1.025 | 0.175 |
| **A4** | 0.825 | 0.236 | -0.025 | 0.971 | 0.236 |

*Source: Test case data*

From Table 6.26, the distances of each alternative to the FPIRP (i.e. $D^{+}$) and FNIRP (i.e. $D^{-}$), and their corresponding CC values are obtained. The results of the sensitivity analysis (i.e. when the input values of the criteria are changed by 10%) are presented in Table 6.27.

**Table 6.25:** Normalised Decision Matrix when Criteria Values are changed

| | **C1** | **C2** | **C3** | **C4** | **C5** |
|---|---|---|---|---|---|
| **A1** | 0.395 | 0.264 | 0.17 | 0.344 | 0.901 |
| **A2** | 0.447 | 0.817 | 0.874 | 0.476 | 0.267 |
| **A3** | 0.567 | 0.467 | 0.454 | 0.588 | 0.203 |
| **A4** | 0.567 | 0.213 | -0.028 | 0.557 | 0.274 |

*Source: Test case data*

**Table 6.26:** Weighted Normalised Decision Matrix when Criteria Values are changed

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| A1 | 0.079 | 0.053 | 0.034 | 0.069 | 0.180 |
| A2 | 0.089 | 0.163 | 0.175 | 0.095 | 0.053 |
| A3 | 0.113 | 0.093 | 0.091 | 0.118 | 0.041 |
| A4 | 0.113 | 0.043 | -0.006 | 0.111 | 0.055 |

*Source: Test case data*

**Table 6.27:** Sensitivity Analysis Results

| | **Decision-Making Attributes** | $D^{+}$ | $D^{-}$ | **CC Values** | **Ranking** |
|---|---|---|---|---|---|
| A1 | Run-to-Failure Maintenance | 0.212 | 0.131 | 0.383 | 4 |
| A2 | Preventive Maintenance | 0.143 | 0.214 | 0.599 | 2 |
| A3 | Condition Based Maintenance | 0.115 | 0.189 | 0.622 | 1 |
| A4 | Reliability-Centred Maintenance | 0.183 | 0.192 | 0.512 | 3 |

*Source: Test case data*

## 6.4 Discussion of Results

In this study, sensitivity analysis is implemented to see the effect in the output data given a slight change in the input data. From the results of the sensitivity analysis (Table 6.25), it can be observed that the ranking order of the four decision alternatives maintained a consistency when the cost category of the criteria (C2, C4, C5) was increased by 10%, and the benefit category (C1, C3) decreased by the same 10%. The analysis reveals that almost all the changes in the criteria input data do not change the final ranking of the maintenance strategies. For this model to be validated, this pattern in the results is to be expected. It can therefore be deduced that the model is reasonable and capable of being applied to the analysis of machinery maintenance strategy decision-making alternatives.

Based on the result obtained from this analysis, the marine machinery (crane) under investigation can be enhanced by implementing A3 (i.e. condition based maintenance) strategy. However, implementing A2 (i.e. preventive maintenance), especially during follow-up analysis (when improving maintenance process), can promote continuous improvement and enhance the crane’s performance under high uncertainty. Experience has shown that investing in maintenance selection strategies seems to be an important strategy to mitigate cost issues under a fuzzy environment. Therefore, the result of the analysis would help improve the decision-making process, thus allowing for a flexible response to operational uncertainties through a systematic approach.

The analysis result reflecting on A3 (condition based maintenance) as the recommended strategy certainly shows that expert judgement was based on increase in machinery operational life/availability, increase in machinery reliability, increase in cost for parts and labour, and decrease in machinery downtime. Minimizing maintenance costs seems to be an effective way to build up efficient maintenance, especially when one is required to work within a limited budget. When investments in maintenance have to be made to reduce the overall costs (i.e., operations costs), it seems logical to consider the minimization of total cost of ownership or the life-cycle costs instead. However, Goossens (2015) ascertained that the ultimate goal of maintenance cannot be cost reduction only and must be maintaining functionality (at the lowest cost). Nevertheless, how costs can best be interpreted in relation to the selection process of the best maintenance strategy remains to be further explored.

The role of safety within the maintenance strategy selection can also be misinterpreted since, according to Goossens (2015), by definition, absolute safety is impossible. As such, safety is considered to act as a pre-condition for maintenance strategy selection. Nevertheless, a balance between safety and availability or reliability can be desirable (or even possible). The exact role that safety currently has within machinery maintenance strategy selection, as well as the role it should have, is worth further investigation. The model developed in this study is by no means conclusive. It is subject to further modification, given the acquisition of new data or before its utilization by end-users in the industry. A sensitivity analysis was conducted to partially validate the developed model and establish its ability to respond to changes in input variables.

### 6.5 Conclusion

This chapter presented a collaborative modelling and strategic FMADM method that can be adopted for the selection of appropriate machinery maintenance strategies in a concise, logical, and transparent manner against multiple scenarios where the data available is subjective and imprecise. The strength of this strategic decision making approach is in the fact that both heterogeneous and homogeneous groups of experts can be utilised and their subjective opinions can be aggregated simply, with partial or incomplete information available.

In the evaluation process, a fuzzy TOPSIS algorithm is implemented to rank the machinery maintenance strategies or alternatives in a way that is flexible and straightforward. To support a strategic decision on machinery maintenance strategy selection, fuzzy AHP and fuzzy TOPSIS need to be utilised to handle multiple organisational objectives, complex decision making, and long term condition of machinery in an uncertain environment. The proposed approach can be applied to situations where both qualitative and quantitative data has to be integrated and synthesized for evaluation processes during complex and multiple decision making involving marine and offshore machinery operations. Since the result of the calculations is sensitive to criteria and the number of experts engaged, these should be carefully chosen by maritime maintenance and safety analysts to avoid misrepresentation and information loss during the interpretation process.

During this study, five factors – *reliability, cost, safety, availability, and downtime* – have converged to create a succinct and effective meaning. However, in practice, the interpretation and relations of these factors differ depending on which experts are involved. The research described in this chapter can serve as a basis to further explore the roles of these factors for selection of an appropriate maintenance strategy. The relation between availability and reliability needs elaboration. Although clear definitions for both are presented in the literature, practitioners seem to have varying interpretations and views of what these two terms mean to their specific situation, and how they are related. To gain a better understanding of the interpretation differences and origin, and how these influence maintenance strategy selection, a structured experimental investigation needs to be considered.

# Chapter 7

## Conclusions and Recommendations

### Summary

This chapter summarises the conceptual frameworks that serve as the basis for the identification of new research needs within the marine and offshore industry, in line with the vision for efficient planned maintenance system for machinery operations. It also highlights the limitations and avenues for future research into areas where traditional maintenance tools cannot be used with confidence, which may require further work to improve the frameworks and methodologies that are systematically developed in this study.

The detailed literature review of machinery operations and maintenance concepts carried out in Chapter 2 provides a deep understanding of the current problematical situation that exists in the marine and offshore industry. The review revealed that although there are a multitude of different machinery planned maintenance programmes employed throughout the industry, there is an equally diverse variety of maintenance strategies utilised in order to ensure successful performance and reliability of the machinery. This thesis draws attention to the problems relating to establishing an optimal planned maintenance framework in the marine and offshore industry, and in doing so, demonstrates a plausible and feasible solution that utilises a risk and decision-based maintenance methodology.

### 7.1 Main Conclusions

An important aspect of this research study is the revelation that a lack of or poor investment in machinery planned maintenance programmes leads to a failing strategy that contributes to the machinery's vulnerabilities and, ultimately, breakdowns. Given the dynamic nature of marine and offshore operations, one feasible way to analyse machinery application in such operations is to use different decision-making tools, which include fuzzy set theory (FST), rule-base (RB), and evidential reasoning (ER), in order to optimize the operational efficiency of the machinery. This research has produced an efficient planned maintenance methodology that leads to the establishment of a platform for improvement of marine and offshore machinery systems that operate under high uncertainties.

This thesis has developed a number of analytical approaches that use qualitative data to measure the multi-dimensional machinery performance. The modelling solutions developed in this study are capable of dealing with both operational and managerial problems. Thus, it can serve as a platform for sustained and enhanced decision-making in a socio-technical system. The use of decision-making analysis to establish efficient maintenance regimes through the evaluation of downtime and costs enables managers to make informed decisions based either on reducing downtime, on reducing costs, or both.

The introduction of trend analysis, family analysis, environmental analysis, human reliability analysis, and design analysis, has highlighted another facet to consider when developing a planned maintenance strategy. The models can not only be applied to the marine and offshore industry, but also to other industries, such as nuclear, aviation, manufacturing, *etc*. The utilisation of multiple tools and approaches in this thesis, to deal with uncertainties in the marine and offshore machinery operations, enables cross validation of the results and increases the confidence in the performed analysis, as ascertained by Patelli *et al*. (2015).

## 7.2 **Advantages and Disadvantages of the Models**

### 7.2.1 Advantages

- The model accommodates multiple analysis (e.g. trend analysis, family analysis, design analysis, environmental analysis, and human reliability analysis) which can provides each marine and offshore operator with correct information relating to equipment inspections, maintenance and repair activities for their maintenance management programme.
- Using calculated baseline in this research is useful for determining of each oil element for all types of machinery.
- The decision-making procedure will be faster and more robust, thus, helps experts to find a suitable solution.
- It is possible to diagnose and predict the final machinery situation for any related database, thus, reduces maintenance-running hours.
- It will be practical to create a database for fault situations and wear behaviours.
- Modelled specifically to address the most relevant deterioration and failure mechanisms, which significantly reduce the number of accident caused by machinery failure in the marine and offshore industry.

### 7.2.2 Disadvantages

- Requires implementation of a sophisticated monitoring system to continuously assess condition and reliability factors

### 7.3 Research Contribution to Knowledge

Machinery systems are increasingly susceptible to malfunctioning caused by unforeseen events that range from new design to man-made errors. As revealed in the literature review (Chapter 2), most sources show that these malfunctions may severely impact on the machinery and result in disruption of their operations with long term consequences. Therefore, through asking the right questions and doing thorough data analysis using existing theories but in a different approach, this research can significantly contribute to knowledge in the following ways:

- The research provides a framework and methodology for machinery condition monitoring that can be applied to marine and offshore as well as other industries (Railway (Fumeo *et al.*, 2015), Nuclear, etc.).
- Applies ER methodology for decision-based making to enrich the insufficient literature of uncertainty treatment within the domain of risk assessment of marine and offshore machinery systems.
- Demonstrates the use of RB theory as a viable risk assessment tool with application to maintenance prediction of machinery operating under highly uncertain environment.
- The generated RB can be applied to a series of real world scenarios to demonstrate the models validity.
- Applies a decision-making algorithm to determine the most suitable maintenance strategy for use within marine and offshore industry.
- The results provided by these algorithms in this study will be beneficial to the marine and offshore industries as an indicator to monitor and diagnose faults in machinery, thus, helping in making a better decision in  maintenance management process.

Finally, this research has been justified as well as adding to existing knowledge by way of contributing solutions to the current machinery oil condition monitoring difficulties in the marine and offshore industry from the findings of the study as well as good recommendations for future research listed in Section 7.7.

### 7.4 Research Findings

- Bearings and gearboxes are found to be the most critical components in ship cranes.

- The reliability of the ship crane will alter if the crane grade decreases from a good grade to an average grade due to inability of the crew on board to carry out maintenance work during bad weather condition.
- Condition based maintenance strategy is the preferred maintenance option for the developed models.

### 7.5 Research Novelty

- This research outlines a novel framework shown in Figure 3.1 for evaluating a ship's crane performance by means of its conditional reliability and the procedure of applying it in a real life scenario.
- The flow diagram (Figure 4.1), the hierarchical structures (Figures 4.2 and 4.9) for evaluating the conditions of the ship cranes; the diagnostic flow chart (Figure 5.1) for evaluating the diagnostic process of the used oil sample test results; and the hierarchical structures (Figures 6.1 and 6.2) for maintenance strategy selection, are all unique and only applicable to this research work.

### 7.6 Research Limitations

The research conducted attempts to highlight a comprehensive and practical analysis of marine and offshore machinery planned maintenance system in relation to risk assessment and improvement of the machinery operations. Due to time constraints, the current study does not investigate a large number of problems and incident scenarios in all the vital components that can lead to machinery breakdown, even though experience has shown that such analysis gives insights into how machinery breakdown can be managed or avoided.

The experience and knowledge proficiencies of experts are vital when the generic frameworks are applied to real industrial case studies, as described in this research, and thus, careful selection of these experts is necessary in order to achieve good outcomes. In other words, if experts who do not have the requisite knowledge or experience are selected and used for the analysis, the frameworks may produce poor outcomes, which may defeat the purpose of improvement and management in the machinery planned maintenance system and render the methodology ineffective.

### 7.7 Recommendation for Future Research

Although this research has provided a structure that links risk assessment and efficient maintenance of offshore marine machinery operating under highly uncertain environments, it has also formulated conceptual frameworks for their efficient planned maintenance systems. The following avenues to further enhance the implementation of the models that can be applied in a different context have been identified:

- Application of the frameworks and models developed to other high reliability industries: it is believed that, if applied to other complex and high reliability industries (e.g. nuclear, aviation, health care, *etc*.) this could give rise to interesting results that may further enrich the deficient literature of planned maintenance modelling for critical machinery.
- Due to the complexity of the analytical results obtained under the conditions of big data, application of computer related software is recommended to facilitate the process of data compilation and processing.
- Within this thesis, four experts were employed to conduct the assessment. However, it is recommended that the number of experts be increased for a collaborative modelling of the system, from a range of different marine and offshore industries, to include chief engineers, 2$^{nd}$ engineers, ship captains, chief officers, maintenance engineers, researchers, marine superintendents, and machinery operators. This will further enhance the collaborative design and effectiveness of the result obtained for use in its wider perspective.
- Combination of diverse but powerful intelligent tools and algorithms from other fields and concepts will open promising new pathways for developing and optimising planned maintenance systems for machinery operations under uncertainty.
- Application of the real-time analysis tool to evaluate the condition of the machinery using the developed models and methodology: such an analysis would enhance the performance and reliability of marine and offshore machinery through early detection of unforeseen events.

This study provides a conceptual platform on which further research on planned maintenance of complex interdependent machinery systems can be modelled and by which the risk of breakdown can be assessed and managed. The traditional ways of looking at such risks are not always suitable for use in assessing the maintenance of complex machinery systems, but a shift towards uncertainty treatment of probability of risk for improvement of the machinery systems can ultimately optimize their operations. Moreover, the methodology demonstrated in this research has been successfully applied to a ship crane operating in the marine and offshore industry. In order to gain greater confidence and insight into the uses and limitations of this methodology, application to other machinery in several industries from differing sectors will need to be attempted.

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# APPENDICES

# Chapter 4 Appendices

## **Appendix 4A -** Experts Ratings

**Table 1-4A**: Expert 1 Rating for Cranes Bearing

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | **X** | | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | **X** | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | **X** | | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | **X** | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | **X** | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | | **X** | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | **X** | | | | | Design Analysis |

**Table 2-4A:** Expert 2 Ratings for Crane Bearing

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute **(9)** | Intermediate **(8)** | Very strong **(7)** | Intermediate **(6)** | Strong **(5)** | Intermediate **(4)** | Weak **(3)** | Intermediate **(2)** | Equal **(1)** | Intermediate **(2)** | Weak **(3)** | Intermediate **(4)** | Strong **(5)** | Intermediate **(6)** | Very strong **(7)** | Intermediate **(8)** | Absolute **(9)** | **Criterion** |
| Trend Analysis | | | | | | | | **X** | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | | | | **X** | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | **X** | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | **X** | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | **X** | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | **X** | | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | **X** | | | | | | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | **X** | | | | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | **X** | | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | **X** | | | | | | Design Analysis |

**Table 3-4A:** Expert 2 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Bearing

| **Crane Bearing** | **TA** | **FA** | **EA** | **HRA** | **DA** | **$5^{th}$ Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 2 | 1 | 6 | 4 | 2.1689 | 0.3328 |
| FA | 0.5 | 1 | 2 | 6 | 6 | 2.0477 | 0.3142 |
| EA | 1 | 0.5 | 1 | 6 | 2 | 1.431 | 0.2196 |
| HRA | 0.1666 | 0.1666 | 0.1666 | 1 | 0.25 | 0.2605 | 0.03998 |
| DA | 0.25 | 0.1666 | 0.5 | 4 | 1 | 0.6083 | 0.0933 |
| SUM | 2.9166 | 3.8332 | 4.6666 | 23 | 13.25 | 6.5164 | **1.0000** |
| SUM * PV | 0.9706 | 1.2044 | 1.0248 | 0.9195 | 1.2362 | **5.3555** | |
| Lambda-max = | 5.3555 | | | | | | |
| CI = | 0.0889 | | | | | | |
| CR = | 0.08 | | | | | | |

**Table 4-4A:** Expert 3 Ratings for Crane Bearing

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | | | **X** | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | **X** | | | | | | | Design Analysis |

**Table 5-4A:** Expert 3 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Bearing

| **Crane Bearing** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 5 | 5 | 5 | 3.6239 | 0.5368 |
| FA | 0.2 | 1 | 0.3333 | 3 | 1 | 0.7247 | 0.1073 |
| EA | 0.2 | 3 | 1 | 3 | 1 | 1.1247 | 0.1666 |
| HRA | 0.2 | 0.3333 | 0.3333 | 1 | 0.3333 | 0.3748 | 0.0555 |
| DA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1337 |
| SUM | 1.8 | 10.3333 | 7.6666 | 15 | 8.3333 | 6.751 | **1.000** |
| SUM * PV | 0.9662 | 1.1088 | 1.2773 | 0.8325 | 1.1142 | **5.299** | |
| Lambda-max = | 5.299 | | | | | | |
| CI = | 0.0748 | | | | | | |
| CR = | 0.07 | | | | | | |

**Table 6-4A:** Expert 4 Ratings for Crane Bearing

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | **X** | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | | | **X** | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | | | | | **X** | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | | | **X** | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | | **X** | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | | | **X** | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | **X** | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | **X** | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | **X** | | | | | | Design Analysis |

**Table 7-4A:** Expert 4 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Bearing

| Crane Bearing | TA | FA | EA | HRA | DA | 5th Root of Component | Priority Vector (PV) |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 4 | 2 | 0.5 | 1.8206 | 0.3014 |
| FA | 0.2 | 1 | 0.3333 | 2 | 0.3333 | 0.5364 | 0.0888 |
| EA | 0.25 | 3 | 1 | 1 | 0.3333 | 0.7579 | 0.1255 |
| HRA | 0.5 | 0.5 | 1 | 1 | 0.25 | 0.5743 | 0.0951 |
| DA | 2 | 3 | 3 | 4 | 1 | 2.3522 | 0.3893 |
| SUM | 3.95 | 12.5 | 9.3333 | 10 | 2.4166 | 6.0414 | **1.000** |
| SUM * PV | 1.1905 | 1.11 | 1.1713 | 0.951 | 0.9408 | **5.3636** | |
| Lambda-max = | 5.3636 | | | | | | |
| CI = | 0.0909 | | | | | | |
| CR = | 0.08 | | | | | | |

**Table 8-4A:** Expert 1 Ratings for Crane Clutch

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Criterion | Absolute **(9)** | Intermediate **(8)** | Very strong **(7)** | Intermediate **(6)** | Strong **(5)** | Intermediate **(4)** | Weak **(3)** | Intermediate **(2)** | Equal **(1)** | Intermediate **(2)** | Weak **(3)** | Intermediate **(4)** | Strong **(5)** | Intermediate **(6)** | Very strong **(7)** | Intermediate **(8)** | Absolute **(9)** | Criterion |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | **X** | | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | **X** | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | **X** | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | **X** | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | **X** | | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | **X** | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | **X** | | | | | Design Analysis |

**Table 9-4A:** Expert 1 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Clutch

| **Crane Clutch** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 6 | 7 | 5 | 4.0201 | 0.5457 |
| FA | 0.2 | 1 | 2 | 5 | 1 | 1.1487 | 0.1559 |
| EA | 0.1666 | 0.5 | 1 | 4 | 0.25 | 0.6083 | 0.0826 |
| HRA | 0.1429 | 0.2 | 0.25 | 1 | 0.2 | 0.2698 | 0.0366 |
| DA | 0.2 | 1 | 4 | 5 | 1 | 1.3195 | 0.1791 |
| SUM | 1.7095 | 7.7 | 13.25 | 22 | 7.45 | 7.3664 | **1.000** |
| SUM * PV | 0.9329 | 1.2004 | 1.0945 | 0.8052 | 1.3343 | **5.3673** | |
| Lambda-max = | 5.3673 | | | | | | |
| CI = | 0.0918 | | | | | | |
| CR = | 0.08 | | | | | | |

**Table 10-4A:** Expert 2 Ratings for Crane Clutch

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | | | | | X | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | X | | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | X | | | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | | X | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | X | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | X | | | | | | | Design Analysis |

**Table 11-4A:** Expert 2 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Clutch

| **Crane Clutch** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5th Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 1 | 5 | 5 | 6 | 2.7241 | 0.415 |
| FA | 1 | 1 | 5 | 5 | 1 | 1.9037 | 0.2900 |
| EA | 0.2 | 0.2 | 1 | 0.5 | 0.3333 | 0.3675 | 0.056 |
| HRA | 0.2 | 0.2 | 2 | 1 | 0.3333 | 0.4845 | 0.0738 |
| DA | 0.1666 | 1 | 3 | 3 | 1 | 1.0844 | 0.1652 |
| SUM | 2.5666 | 3.4 | 16 | 14.5 | 8.6666 | 6.5642 | **1.000** |
| SUM * PV | 1.0651 | 0.986 | 0.896 | 1.0701 | 1.4317 | **5.4489** | |
| Lambda-max = | 5.4489 | | | | | | |
| CI = | 0.1122 | | | | | | |
| CR = | 0.1 | | | | | | |

**Table 12-4A:** Expert 3 Ratings for Crane Clutch

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | **X** | | | | | | | Design Analysis |

**Table 13-4A:** Expert 3 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Clutch

| **Crane Clutch** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5th Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 5 | 5 | 5 | 3.6239 | 0.5403 |
| FA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1346 |
| EA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1346 |
| HRA | 0.2 | 0.3333 | 0.3333 | 1 | 0.3333 | 0.3748 | 0.0559 |
| DA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1346 |
| SUM | 1.8 | 8.3333 | 8.3333 | 15 | 8.3333 | 6.7074 | **1.000** |
| SUM * PV | 0.9725 | 1.1217 | 1.1217 | 0.8385 | 1.1217 | **5.1761** | |
| Lambda-max = | 5.1761 | | | | | | |
| CI = | 0.044 | | | | | | |
| CR = | 0.04 | | | | | | |

**Table 14-4A:** Expert 4 Ratings for Crane Clutch

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | | **X** | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | **X** | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | **X** | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | | **X** | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | | **X** | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | **X** | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | **X** | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | **X** | | | | | | | Design Analysis |

**Table 15-4A:** Expert 4 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Clutch

| **Crane Clutch** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 3 | 4 | 4 | 2.9926 | 0.4744 |
| FA | 0.2 | 1 | 1 | 2 | 0.5 | 0.7248 | 0.1149 |
| EA | 0.3333 | 1 | 1 | 2 | 0.25 | 0.6989 | 0.1108 |
| HRA | 0.25 | 0.5 | 0.5 | 1 | 0.3333 | 0.4609 | 0.0731 |
| DA | 0.25 | 2 | 4 | 3 | 1 | 1.431 | 0.2268 |
| SUM | 2.0333 | 9.5 | 9.5 | 12 | 6.0833 | 6.3082 | **1.000** |
| SUM * PV | 0.9646 | 1.0916 | 1.0526 | 0.8772 | 1.3797 | **5.3657** | |
| Lambda-max = | 5.3657 | | | | | | |
| CI = | 0.0914 | | | | | | |
| CR = | 0.08 | | | | | | |

**Table 16-4A:** Expert 1 Ratings for Crane Gearbox

| | **Scale of relative importance** | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute **(9)** | Intermediate **(8)** | Very strong **(7)** | Intermediate **(6)** | Strong **(5)** | Intermediate **(4)** | Weak **(3)** | Intermediate **(2)** | Equal **(1)** | Intermediate **(2)** | Weak **(3)** | Intermediate **(4)** | Strong **(5)** | Intermediate **(6)** | Very strong **(7)** | Intermediate **(8)** | Absolute **(9)** | **Criterion** |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | **X** | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | **X** | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | **X** | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | **X** | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | **X** | | | | | | Design Analysis |

**Table 17-4A:** Expert 1 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Gearbox

| **Crane Gearbox** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 5 | 8 | 5 | 3.9811 | 0.5493 |
| FA | 0.2 | 1 | 3 | 5 | 1 | 1.2457 | 0.1719 |
| EA | 0.2 | 0.3333 | 1 | 3 | 0.5 | 0.6308 | 0.087 |
| HRA | 0.125 | 0.2 | 0.3333 | 1 | 0.25 | 0.2914 | 0.0402 |
| DA | 0.2 | 1 | 2 | 4 | 1 | 1.0986 | 0.1516 |
| SUM | 1.725 | 7.5333 | 11.3333 | 21 | 7.75 | 7.2476 | **1.000** |
| SUM * PV | 0.9475 | 1.295 | 0.986 | 0.8442 | 1.1749 | **5.2476** | |
| Lambda-max = | 5.2476 | | | | | | |
| CI = | 0.0619 | | | | | | |
| CR = | 0.05 | | | | | | |

## Table 18-4A: Expert 2 Ratings for Crane Gearbox

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Criterion | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | Criterion |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | X | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | X | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | X | | | | | | | Design Analysis |

**Table 19-4A:** Expert 2 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Gearbox

| Crane Gearbox | TA | FA | EA | HRA | DA | 5th Root of Component | Priority Vector (PV) |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 4 | 7 | 4 | 3.5452 | 0.5288 |
| FA | 0.2 | 1 | 1 | 5 | 1 | 1 | 0.1492 |
| EA | 0.25 | 1 | 1 | 2 | 1 | 0.8706 | 0.1299 |
| HRA | 0.1429 | 0.2 | 0.5 | 1 | 0.3333 | 0.3438 | 0.0513 |
| DA | 0.25 | 1 | 1 | 3 | 1 | 0.9441 | 0.1408 |
| SUM | 1.8429 | 8.2 | 7.5 | 18 | 7.3333 | 6.7037 | **1.000** |
| SUM * PV | 0.9745 | 1.2234 | 0.9743 | 0.923 | 1.0325 | **5.1277** | |
| Lambda-max = | 5.1277 | | | | | | |
| CI = | 0.0319 | | | | | | |
| CR = | 0.03 | | | | | | |

**Table 20-4A:** Expert 3 Ratings for Crane Gearbox

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute **(9)** | Intermediate **(8)** | Very strong **(7)** | Intermediate **(6)** | Strong **(5)** | Intermediate **(4)** | Weak **(3)** | Intermediate **(2)** | Equal **(1)** | Intermediate **(2)** | Weak **(3)** | Intermediate **(4)** | Strong **(5)** | Intermediate **(6)** | Very strong **(7)** | Intermediate **(8)** | Absolute **(9)** | **Criterion** |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | **X** | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | **X** | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | **X** | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | **X** | | | | | | Design Analysis |

**Table 21-4A:** Expert 3 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Gearbox

| **Crane Gearbox** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5$^{th}$ Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 5 | 5 | 5 | 3.6239 | 0.5376 |
| FA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1339 |
| EA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1339 |
| HRA | 0.2 | 0.3333 | 0.3333 | 1 | 0.25 | 0.3545 | 0.0526 |
| DA | 0.2 | 1 | 1 | 4 | 1 | 0.9564 | 0.1419 |
| SUM | 1.8 | 8.3333 | 8.3333 | 16 | 8.25 | 6.7406 | **1.000** |
| SUM * PV | 0.9677 | 1.1158 | 1.1158 | 0.8416 | 1.1707 | **5.2116** | |
| Lambda-max = | 5.2116 | | | | | | |
| CI = | 0.0529 | | | | | | |
| CR = | 0.05 | | | | | | |

**Table 22-4A: Expert 4 Ratings for Crane Gearbox**

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | | X | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | X | | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | X | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | X | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | X | | | | | Design Analysis |

**Table 23-4A:** Expert 4 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Gearbox

| **Crane Gearbox** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5th Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 4 | 5 | 5 | 3 | 3.1291 | 0.4624 |
| FA | 0.25 | 1 | 4 | 5 | 1 | 1.3797 | 0.2039 |
| EA | 0.2 | 0.25 | 1 | 1 | 0.25 | 0.4163 | 0.0615 |
| HRA | 0.2 | 0.2 | 1 | 1 | 0.2 | 0.3807 | 0.0563 |
| DA | 0.3333 | 1 | 4 | 5 | 1 | 1.4614 | 0.2160 |
| SUM | 1.9833 | 6.45 | 15 | 17 | 5.45 | 6.7672 | **1.000** |
| SUM * PV | 0.9171 | 1.3152 | 0.9225 | 0.9571 | 1.1772 | **5.2891** | |
| Lambda-max = | 5.2891 | | | | | | |
| CI = | 0.0723 | | | | | | |
| CR = | 0.06 | | | | | | |

**Table 24-4A: Expert 1 Ratings for Crane Hydraulic Pump**

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | X | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | X | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | X | | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | X | | | | | Design Analysis |

**Table 25-4A:** Expert 1 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Hydraulic Pump

| **Crane Hydraulic Pump** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5th Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 4 | 4 | 5 | 5 | 3.3145 | 0.4973 |
| FA | 0.25 | 1 | 3 | 5 | 1 | 1.3026 | 0.1954 |
| EA | 0.25 | 0.3333 | 1 | 3 | 2 | 0.8706 | 0.1306 |
| HRA | 0.2 | 0.2 | 0.3333 | 1 | 0.2 | 0.3064 | 0.046 |
| DA | 0.2 | 1 | 0.5 | 5 | 1 | 0.8706 | 0.1306 |
| SUM | 1.9 | 6.5333 | 8.8333 | 19 | 9.2 | 6.6647 | **1.000** |
| SUM * PV | 0.9449 | 1.2766 | 1.1536 | 0.874 | 1.2015 | **5.4506** | |
| Lambda-max = | 5.4506 | | | | | | |
| CI = | 0.1127 | | | | | | |
| CR = | 0.1 | | | | | | |

## TABLE 26-4A: Expert 2 Ratings for Crane Hydraulic Pump

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | | X | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | X | | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | X | | | | | | Design Analysis |

**Table 27-4A:** Expert 2 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Hydraulic Pump

| **Crane Hydraulic Pump** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5th Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 4 | 3 | 4 | 2.9926 | 0.473 |
| FA | 0.2 | 1 | 1 | 5 | 1 | 1 | 0.1580 |
| EA | 0.25 | 1 | 1 | 4 | 1 | 1 | 0.1580 |
| HRA | 0.3333 | 0.2 | 0.25 | 1 | 0.25 | 0.3347 | 0.0529 |
| DA | 0.25 | 1 | 1 | 4 | 1 | 1 | 0.1580 |
| SUM | 2.0333 | 8.2 | 7.25 | 17 | 7.25 | 6.3273 | **1.000** |
| SUM * PV | 0.9618 | 1.2956 | 1.1455 | 0.8993 | 1.1455 | **5.4477** | |
| Lambda-max = | 5.4477 | | | | | | |
| CI = | 0.1119 | | | | | | |
| CR = | 0.1 | | | | | | |

**Table 28-4A: Expert 3 Ratings for Crane Hydraulic Pump**

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | X | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | X | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | X | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | X | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | X | | | | | | | Design Analysis |

**Table 29-4A:** Expert 3 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Hydraulic Pump

| **Crane Hydraulic Pump** | **TA** | **FA** | **EA** | **HRA** | **DA** | **5th Root of Component** | **Priority Vector (PV)** |
|---|---|---|---|---|---|---|---|
| TA | 1 | 5 | 5 | 5 | 5 | 3.6239 | 0.5403 |
| FA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1346 |
| EA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1346 |
| HRA | 0.2 | 0.3333 | 0.3333 | 1 | 0.3333 | 0.3748 | 0.0559 |
| DA | 0.2 | 1 | 1 | 3 | 1 | 0.9029 | 0.1346 |
| SUM | 1.8 | 8.3333 | 8.3333 | 15 | 8.3333 | 6.7074 | **1.000** |
| SUM * PV | 0.9725 | 1.1217 | 1.1217 | 0.8385 | 1.1217 | **5.1761** | |
| Lambda-max = | 5.1751 | | | | | | |
| CI = | 0.044 | | | | | | |
| CR = | 0.04 | | | | | | |

**Table 30-4A: Expert 4 Ratings for Crane Hydraulic Pump**

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Criterion** | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | **Criterion** |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | X | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | | X | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | | | X | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | X | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | X | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | X | | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | X | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | X | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | X | | | | | | | | Design Analysis |

**Table 31-4A:** Expert 4 Pair-wise Comparison Matrix and Developing the Rating for each Decision Alternative for the Crane Hydraulic Pump

| Crane Hydraulic Pump | TA | FA | EA | HRA | DA | 5th Root of Component | Priority Vector (PV) |
|---|---|---|---|---|---|---|---|
| TA | 1 | 4 | 4 | 3 | 2 | 2.4915 | 0.4135 |
| FA | 0.25 | 1 | 3 | 4 | 2 | 1.431 | 0.2375 |
| EA | 0.25 | 0.3333 | 1 | 1 | 0.3333 | 0.4884 | 0.0811 |
| HRA | 0.3333 | 0.25 | 1 | 1 | 0.5 | 0.5297 | 0.0879 |
| DA | 0.5 | 0.5 | 3 | 2 | 1 | 1.0845 | 0.180 |
| SUM | 2.3333 | 6.0833 | 12 | 11 | 5.8333 | 6.0251 | **1.000** |
| SUM * PV | 0.9648 | 1.4448 | 0.9732 | 0.9669 | 1.05 | **5.3997** | |
| Lambda-max = | 5.3997 | | | | | | |
| CI = | 0.0999 | | | | | | |
| CR = | 0.09 | | | | | | |

# **Appendix 4B -** Evaluation of Trend Analysis

## 4B1 – Membership Functions for Crane Bearing Grease Sample Elements

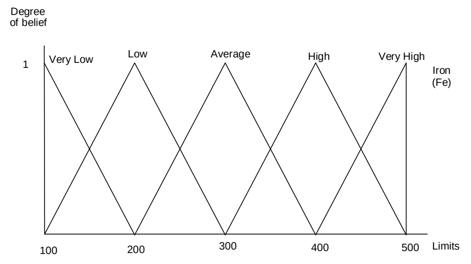


Figure 1-4B1: Membership Function of the Iron (Fe) Element

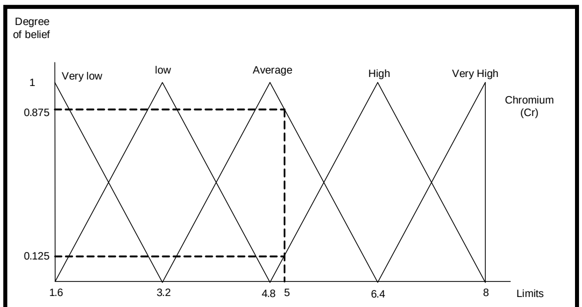


Figure 2-4B1: Membership Function of the Chromium (Cr) Element

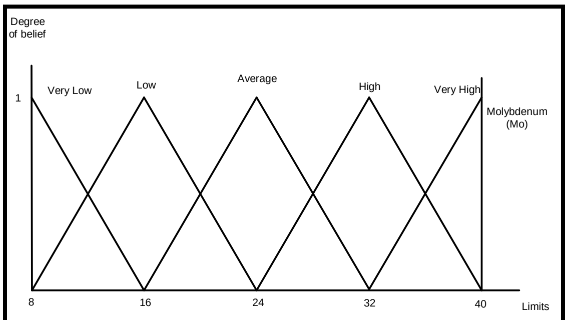


Figure 3-4B1: Membership Function of the Molybdenum (Mo) Element

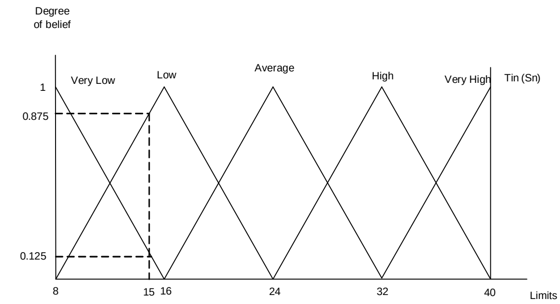


Figure 4-4B1: Membership Function of the Tin (Sn) Element

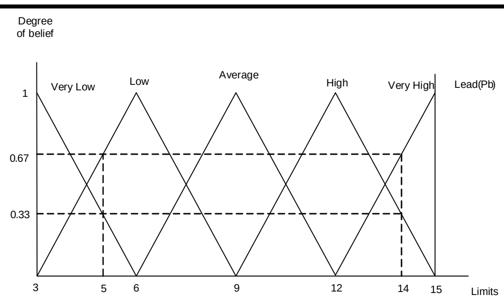


Figure 5-4B1: Membership Function of the Lead (Pb) Element

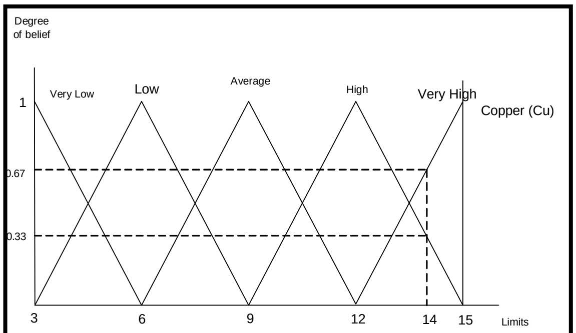


Figure 6-4B1: Membership Function of the Copper (Cu) Element

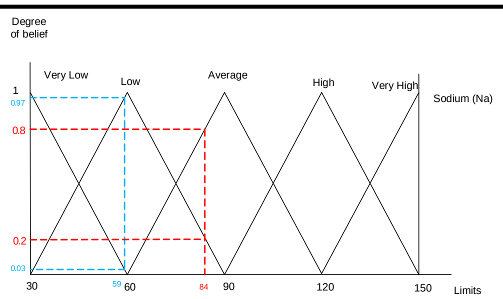


Figure 7-4B1: Membership Function of the Sodium (Na) Element

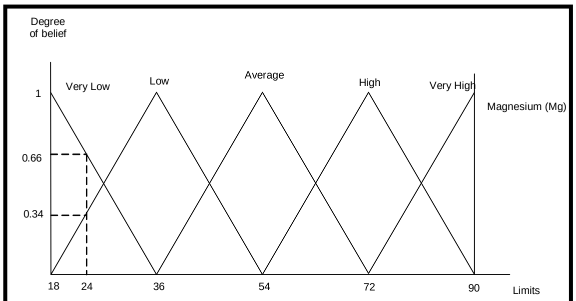


Figure 8-4B1: Membership Function of the Magnesium (Mg) Element

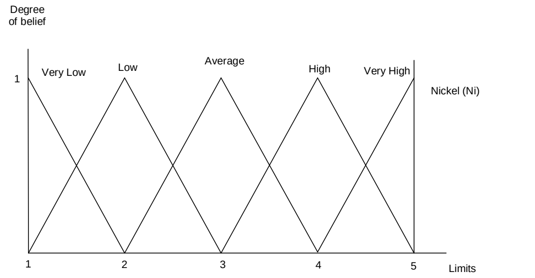


Figure 9-4B1: Membership Function of the Nickel (Ni) Element

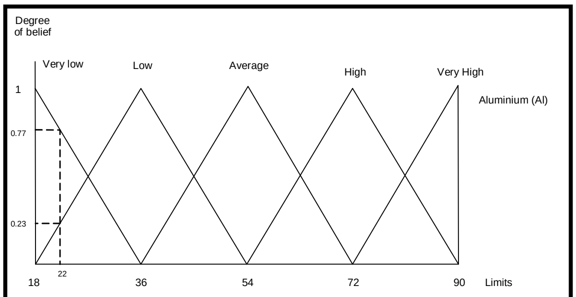


Figure 10-4B1: Membership Function of the Aluminium (Al) Element

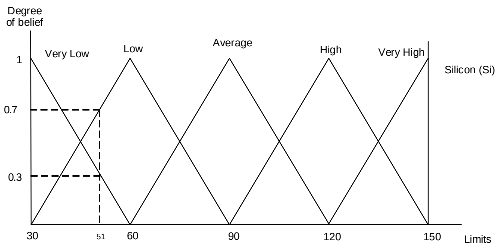


Figure 11-4B1: Membership Function of the Silicon (Si) Element

## 4B2 – Membership Functions for Crane Clutch Oil Sample Elements

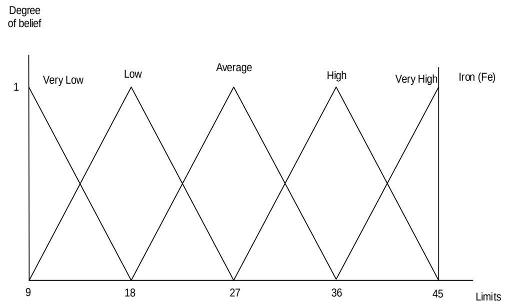


Figure 1-4B2: Membership Function of the Iron (Fe) Element

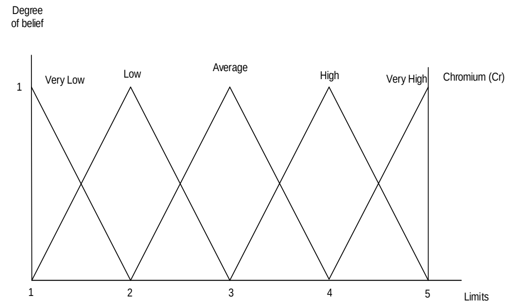


Figure 2-4B2: Membership Function of the Chromium (Cr) Element

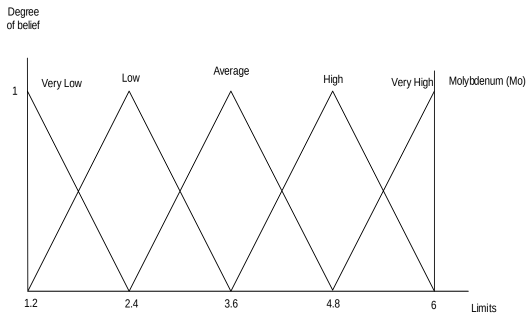


Figure 3-4B2: Membership Function of the Molybdenum (Mo) Element

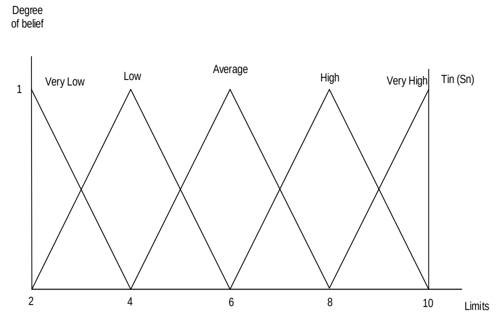


Figure 4-4B2: Membership Function of the Tin (Sn) Element

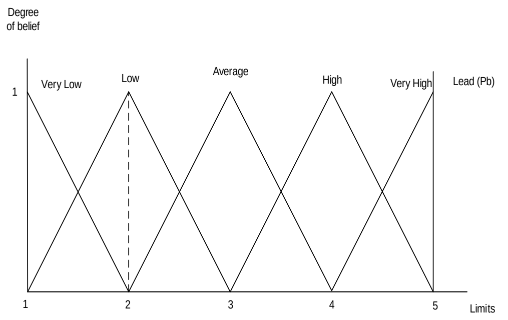


Figure 5-4B2: Membership Function of the Lead (Pb) Element

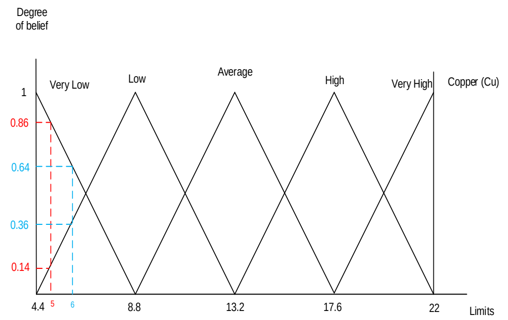


Figure 6-4B2: Membership Function of the Copper (Cu) Element

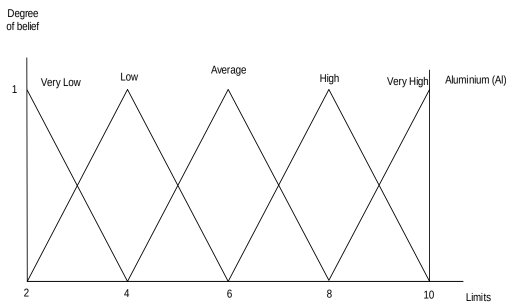


Figure 7-4B2: Membership Function of the Aluminium (Al) Element

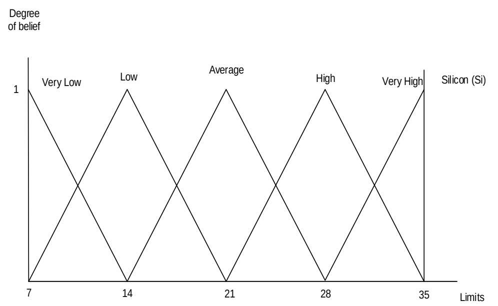


Figure 8-4B2: Membership Function of the Silicon (Si) Element

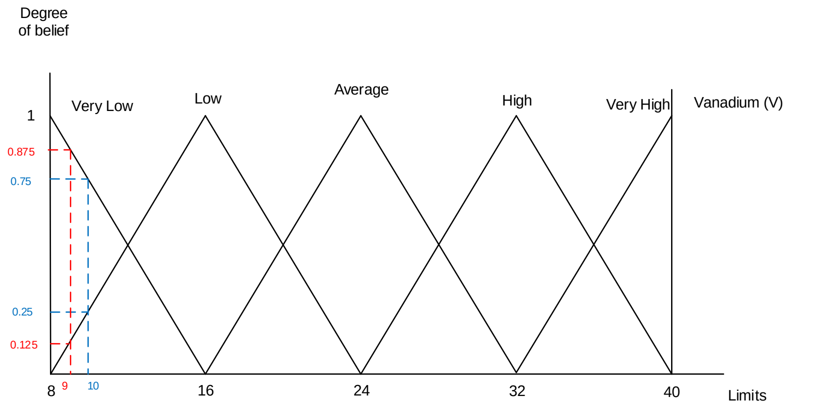


Figure 9-4B2: Membership Function of the Vanadium (V) Element

# 4B3 – Membership Functions for Crane Gearbox Oil Sample Elements

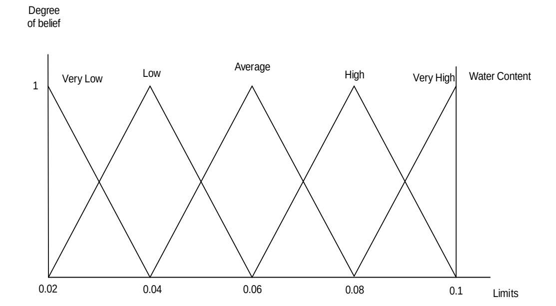


Figure 1-4B3: Membership Function of Water Content

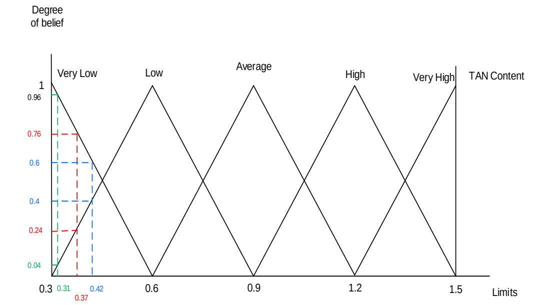


Figure 2-4B3: Membership Function of TAN Content

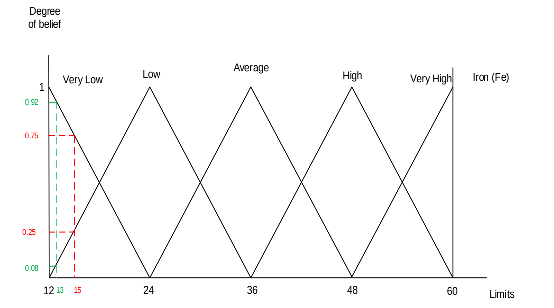


Figure 3-4B3: Membership Function of the Iron (Fe) Element

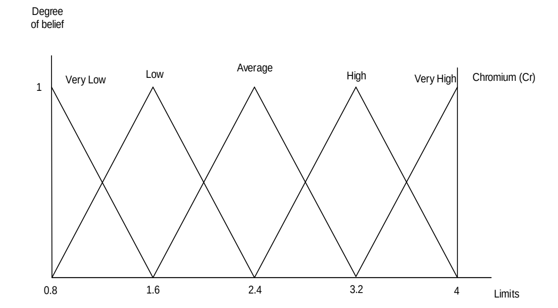


Figure 4-4B3: Membership Function of the Chromium (Cr) Element

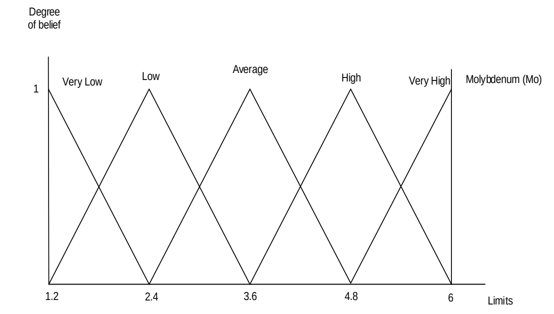


Figure 5-4B3: Membership Function of the Molybdenum (Mo) Element

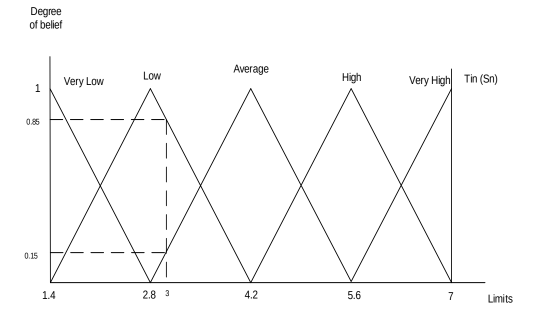


Figure 6-4B3: Membership Function of the Tin (Sn) Element

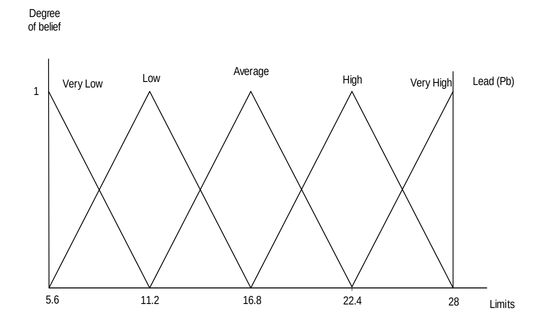


Figure 7-4B3: Membership Function of the Lead (Pb) Element

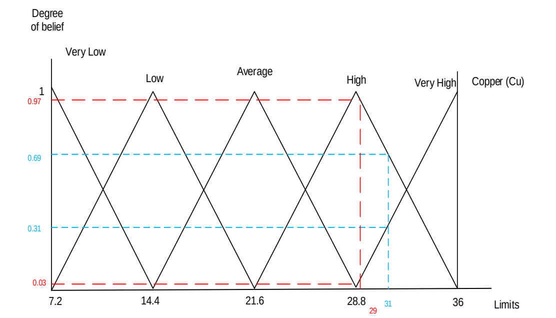


Figure 8-4B3: Membership Function of the Copper (Cu) Element

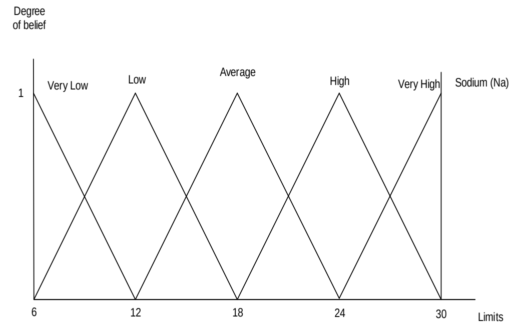


Figure 9-4B3: Membership Function of the Sodium (Na) Element

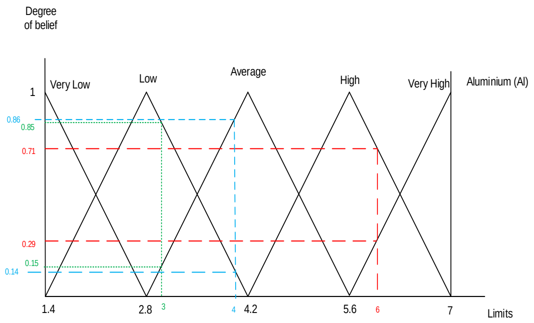


Figure 10-4B3: Membership Function of the Aluminium (Al) Element

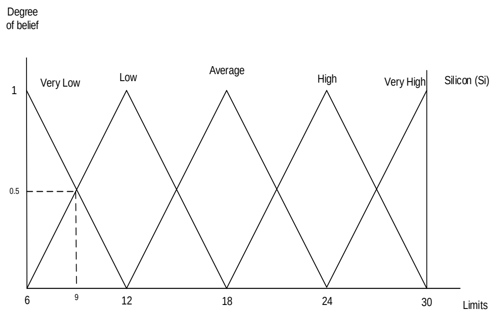


Figure 11-4B3: Membership Function of the Silicon (Si) Element

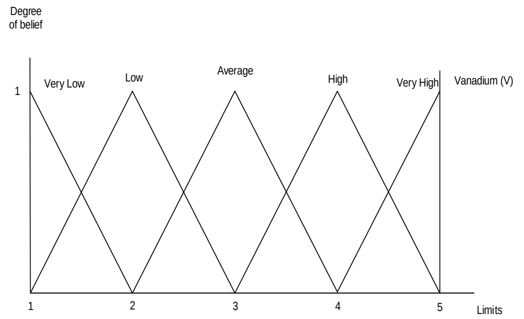


Figure 12-4B3: Membership Function of the Vanadium (V) Element

# 4B4 – Membership Functions for Crane Hydraulic Pump Oil Sample Elements

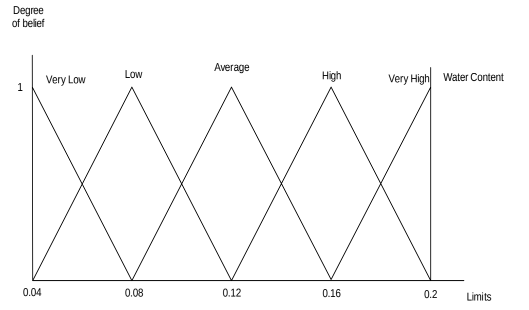


Figure 1-4B4: Membership Function of Water Content

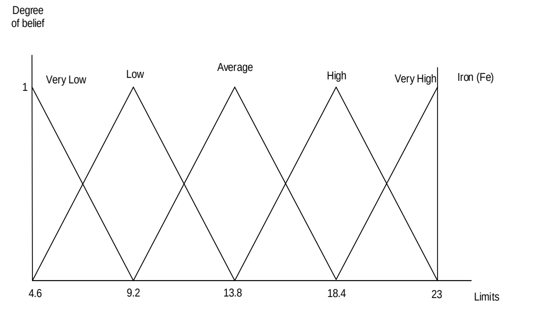


Figure 2-4B4: Membership Function of the Iron (Fe) Element

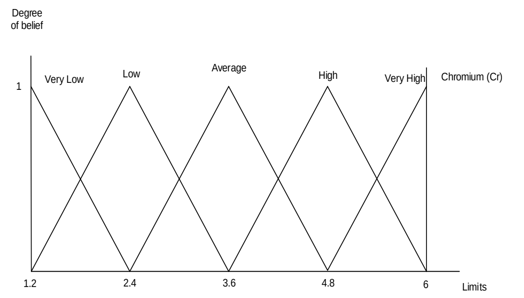


Figure 3-4B4: Membership Function of the Chromium (Cr) Element

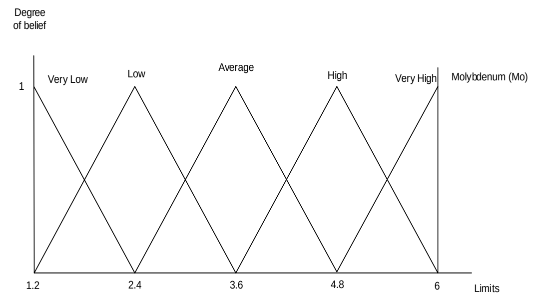


Figure 4-4B4: Membership Function of the Molybdenum (Mo) Element

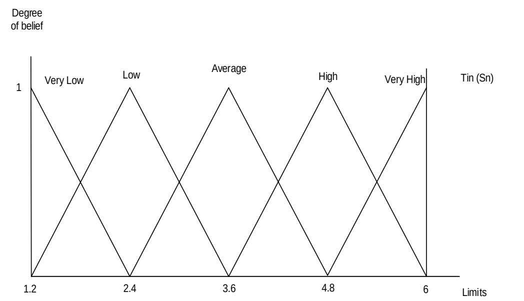


Figure 5-4B4: Membership Function of the Tin (Sn) Element

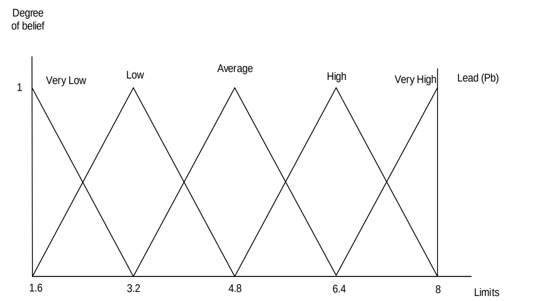


Figure 6-4B4: Membership Function of the Lead (Pb) Element

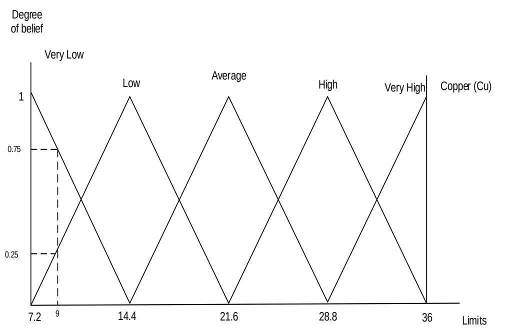


Figure 7-4B4: Membership Function of the Copper (Cu) Element

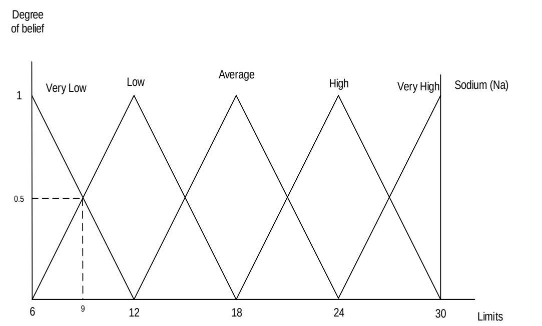


Figure 8-4B4: Membership Function of the Sodium (Na) Element

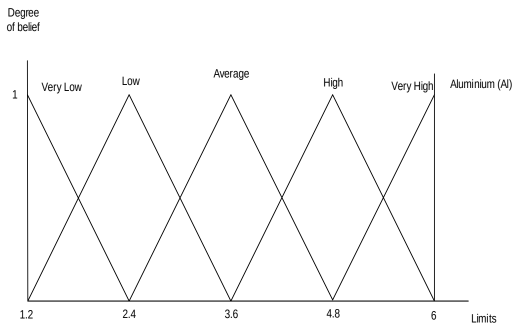


Figure 9-4B4: Membership Function of the Aluminium (Al) Element

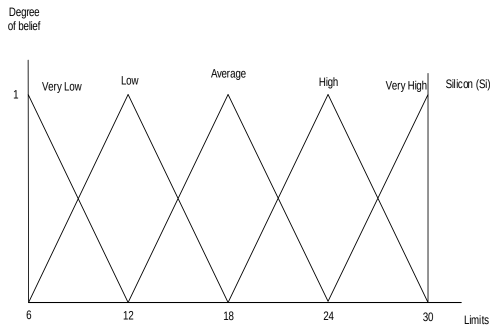


Figure 10-4B4: Membership Function of the Silicon (Si) Element

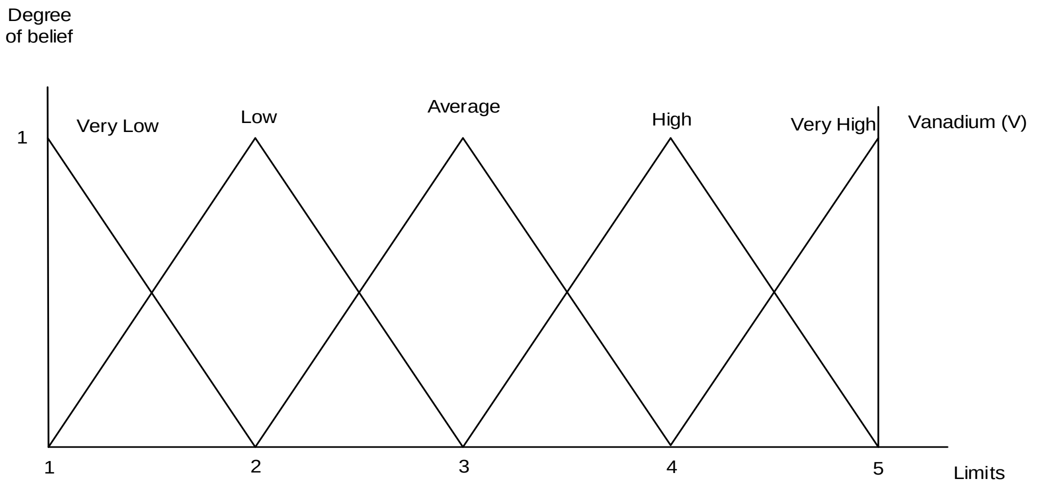


Figure 11-4B4: Membership Function of the Vanadium (V) Element

# **Appendix 4C -** Evaluation of Family Analysis

## 4C1 – Membership Functions for Crane Bearing Grease Sample Elements

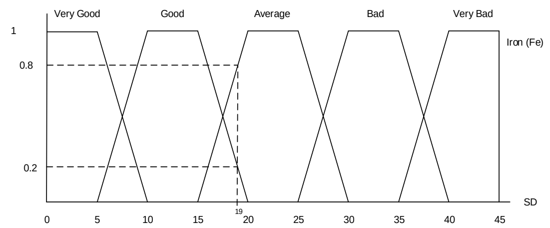


Figure 1-4C1: Membership Function of the Iron (Fe) Element

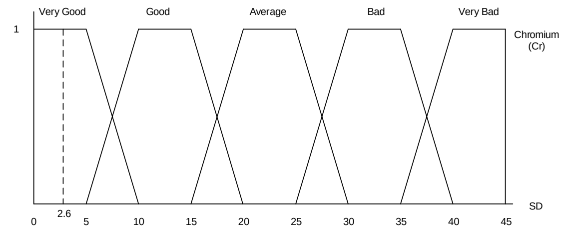


Figure 2-4C1: Membership Function of the Chromium (Cr) Element

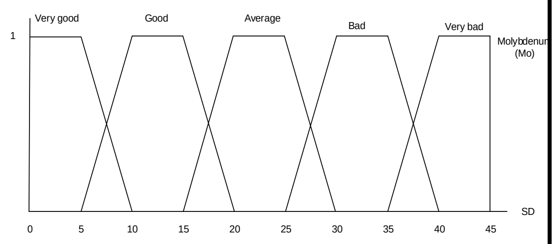


Figure 3-4C1: Membership Function of the Molybdenum (Mo) Element

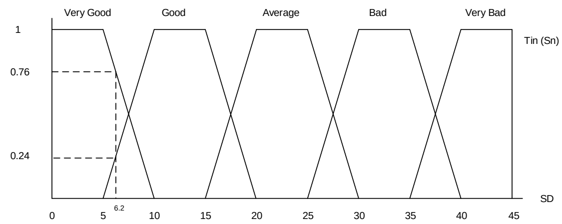


Figure 4-4C1: Membership Function of the Tin (Sn) Element

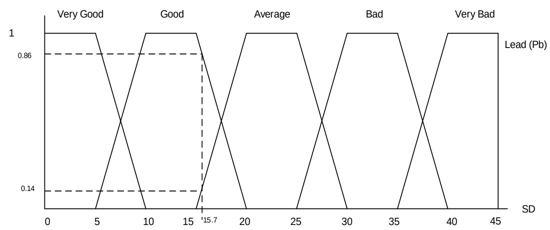


Figure 5-4C1: Membership Function of the Lead (Pb) Element


Figure 6-4C1: Membership Function of the Copper (Cu) Element

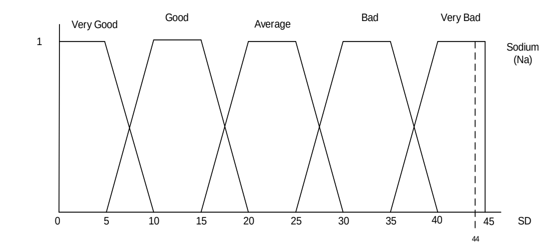


Figure 7-4C1: Membership Function of the Sodium (Na) Element


Figure 8-4C1: Membership Function of the Magnesium (Mg) Element

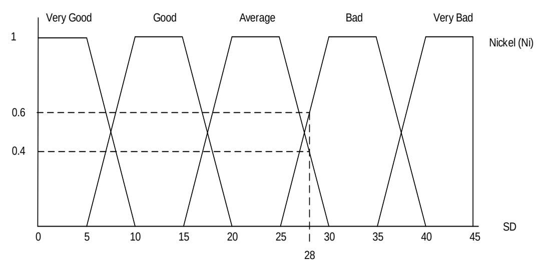


Figure 9-4C1: Membership Function of the Nickel (Ni) Element


Figure 10-4C1: Membership Function of the Aluminium (Al) Element

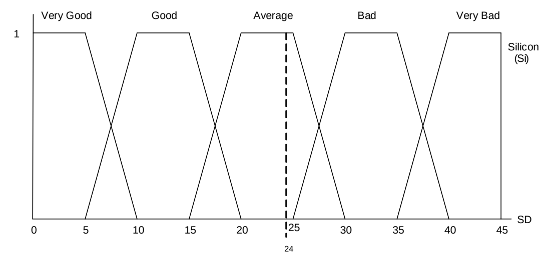


Figure 11-4C1: Membership Function of the Silicon (Si) Element

# 4C2 – Membership Functions for Crane Clutch Oil Sample Elements


Figure 1-4C2: Membership Function of the Iron (Fe) Element


Figure 2-4C2: Membership Function of Chromium (Cr)Element

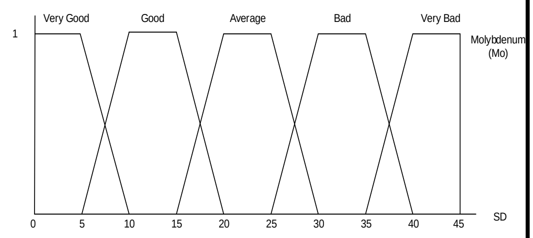


Figure 3-4C2: Membership Function of the Molybdenum (Mo) Element

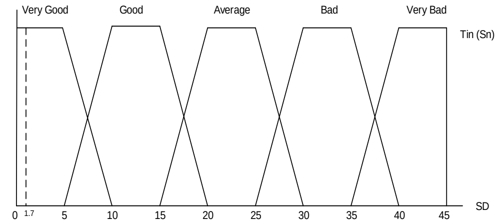


Figure 4-4C2: Membership Function of Tin (Sn) Element


Figure 5-4C2: Membership Function of Lead (Pb) Element

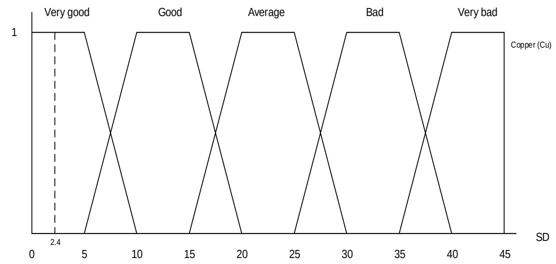


Figure 6-4C2: Membership Function of the Copper (Cu) Element

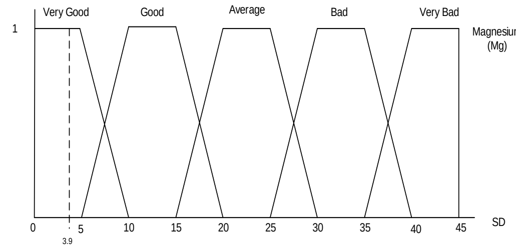


Figure 7-4C2: Membership Function of Magnesium (Mg) Element

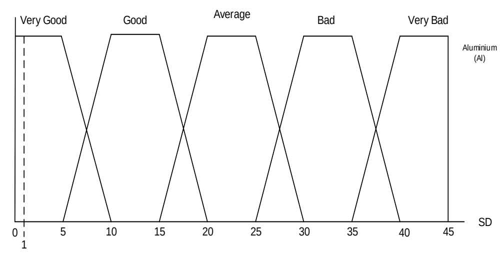


Figure 8-4C2: Membership Function of Aluminium (Al) Element

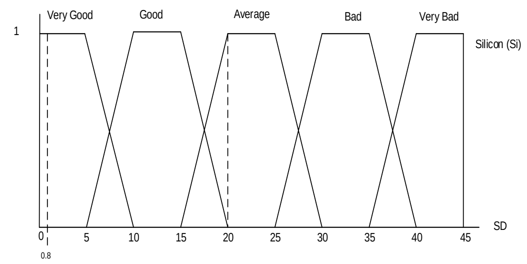


Figure 9-4C2: Membership Function of Silicon (Si) Element


Figure 10-4C2: Membership Function of Vanadium and (V) Element

# 4C3 – Membership Functions for Crane Gearbox Oil Sample Elements

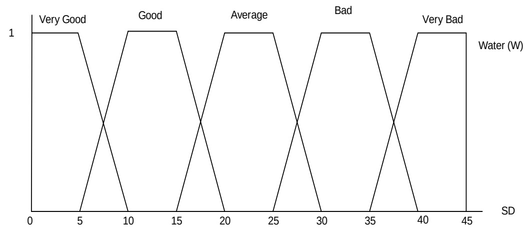


Figure 1-4C3: Membership Function of the Water (W) Element

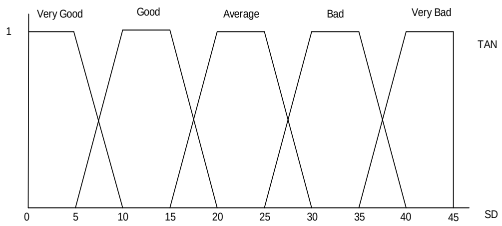


Figure 2-4C3: Membership Function of the TAN Element

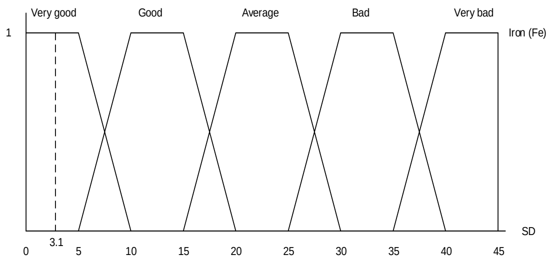


Figure 3-4C3: Membership Function of Iron (Fe) Element


Figure 4-4C3: Membership Function of Chromium (Cr) Element


Figure 5-4C3: Membership Function of Molybdenum (Mo) Element

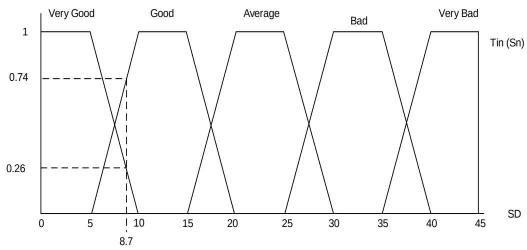


Figure 6-4C3: Membership Function of Tin (Sn) Element


Figure 7-4C3: Membership Function of Lead (Pb) Element


Figure 8-4C3: Membership Function of Copper (Cu) Element

Figure 9-4C3: Membership Function of Sodium (Na) Element

Figure 10-4C3: Membership Function of Magnesium (Mg) Element

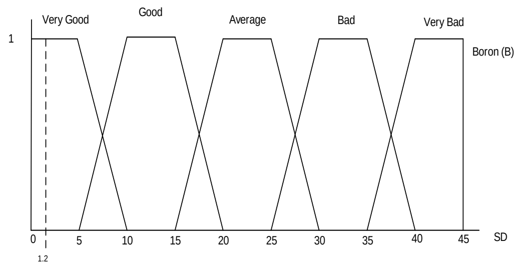

Figure 11-4C3: Membership Function of Boron (B) Element

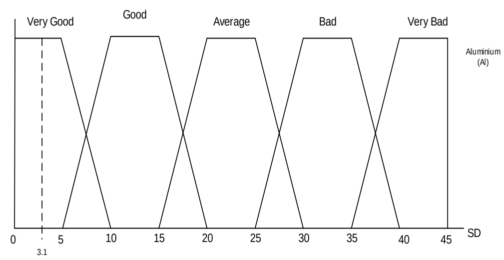

Figure 12-4C3: Membership Function of Aluminium (Al) Element

Figure 13-4C3: Membership Function of Silicon (Si) Element

Figure 14-4C3: Membership Function of Vanadium (V) Element

# 4C4 – Membership Functions for Crane Hydraulic Pump Oil Sample Elements


Figure 1-4C4: Membership Function of Water (W) Element


Figure 2-4C4: Membership Function of TAN Element

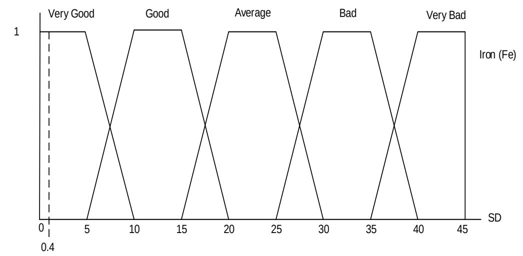


Figure 3-4C4: Membership Function of Iron (Fe) Element


Figure 4-4C4: Membership Function of Chromium (Cr) Element


Figure 5-4C4: Membership Function of Molybdenum (Mo) Element


Figure 6-4C4: Membership Function of Tin (Sn) Element


Figure 7-4C4: Membership Function of Lead (Pb) Element

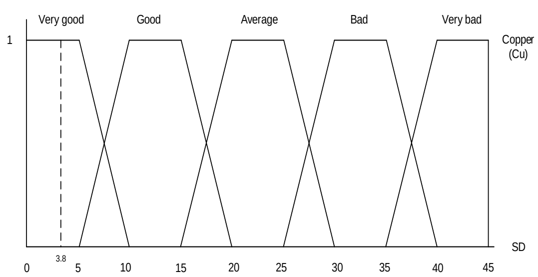


Figure 8-4C4: Membership Function of the Copper (Cu) Element

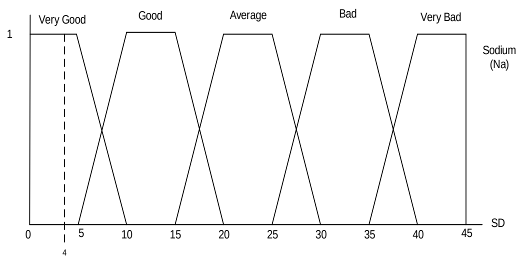


Figure 9-4C4: Membership Function of Sodium (Na) Element


Figure 10-4C4: Membership Function of Magnesium (Mg) Element

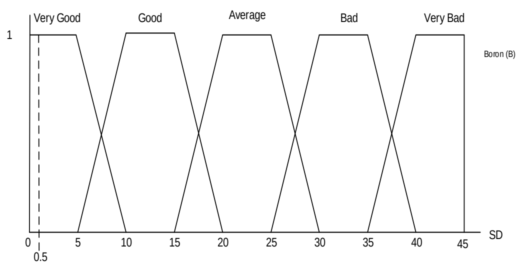


Figure 11-4C4: Membership Function of Boron (B) Element

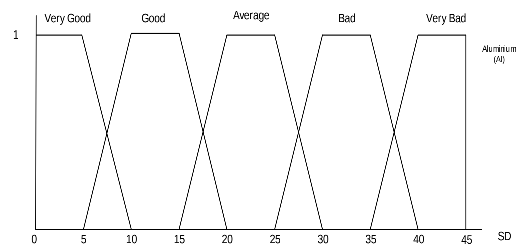


Figure 12-4C4: Membership Function of Aluminium (Al) Element


Figure 13-4C4: Membership Function of Silicon (Si) Element

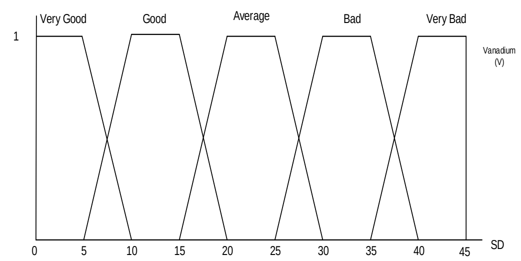


Figure 14-4C4: Membership Function of Vanadium (V) Element

## Appendix 4D - Aggregation of Sub-Criteria

**Table 1 – 4D:** Aggregation of Sub-Criteria for Crane Bearing Sample 1

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_1$, $FA_B$, HR, DA | {(0.1914, Very Bad), (0.0449, Bad), (0.0761, Average), (0.1693, Good), (0.5183, Very Good)} |
| $E_2$ , $TA_1$, $FA_B$, HR, DA | {(0.1977, Very Bad), (0.0463, Bad), (0.0787, Average), (0.3266, Good), (0.3507, Very Good)} |
| $E_3$ , $TA_1$, $FA_B$, HR, DA | {(0.2014, Very Bad), (0.0472, Bad), (0.2162, Average), (0.1781, Good), (0.3572, Very Good)} |
| $E_4$ , $TA_1$, $FA_B$, HR, DA | {(0.2026, Very Bad), (0.1782, Bad), (0.0806, Average), (0.1792, Good), (0.3594, Very Good)} |
| $E_5$ , $TA_1$, $FA_B$, HR, DA | {(0.3522, Very Bad), (0.0461, Bad), (0.0783, Average), (0.1742, Good), (0.3492, Very Good)} |
| **Aggregation result (main criteria) $B_1$** | **{(0.2251, Very Bad), (0.0658, Bad), (0.0978, Average), (0.1996, Good), (0.4117, Very Good)}** |

**Table 2 – 4D:** Aggregation of Sub-Criteria for Crane Clutch Sample 1

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_1$, $FA_C$, HR, DA | {(0.0053, Very Bad), (0.0063, Bad), (0.0140, Average), (0.1685, Good), (0.8060, Very Good)} |
| $E_2$ , $TA_1$, $FA_C$, HR, DA | {(0.0056, Very Bad), (0.0066, Bad), (0.0147, Average), (0.2476, Good), (0.7255, Very Good)} |
| $E_3$ , $TA_1$, $FA_C$, HR, DA | {(0.0057, Very Bad), (0.0067, Bad), (0.0697, Average), (0.1805, Good), (0.7373, Very Good)} |
| $E_4$ , $TA_1$, $FA_C$, HR, DA | {(0.0057, Very Bad), (0.0607, Bad), (0.0150, Average), (0.1806, Good), (0.7379, Very Good)} |
| $E_5$ , $TA_1$, $FA_C$, HR, DA | {(0.0596, Very Bad), (0.0067, Bad), (0.0150, Average), (0.1807, Good), (0.7380, Very Good)} |
| **Aggregation result (main criteria) $C_1$** | **{(0.0121, Very Bad), (0.0129, Bad), (0.0191, Average), (0.1552, Good), (0.8006, Very Good)}** |

**Table 3 – 4D:** Aggregation of Sub-Criteria for Crane Gearbox Sample 1

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_1$, $FA_G$, HR, DA | {(0.1569, Very Bad), (0.0338, Bad), (0.0118, Average), (0.1582, Good), (0.6392, Very Good)} |
| $E_2$ , $TA_1$, $FA_G$, HR, DA | {(0.1636, Very Bad), (0.0352, Bad), (0.0123, Average), (0.2430, Good), (0.5458, Very Good)} |
| $E_3$ , $TA_1$, $FA_G$, HR, DA | {(0.1664, Very Bad), (0.0359, Bad), (0.0748, Average), (0.1677, Good), (0.5552, Very Good)} |
| $E_4$ , $TA_1$, $FA_G$, HR, DA | {(0.1660, Very Bad), (0.1005, Bad), (0.0125, Average), (0.1673, Good), (0.5538, Very Good)} |
| $E_5$ , $TA_1$, $FA_G$, HR, DA | {(0.2416, Very Bad), (0.0353, Bad), (0.0123, Average), (0.1649, Good), (0.5459, Very Good)} |
| **Aggregation result (main criteria) $G_1$** | **{(0.1602, Very Bad), (0.0403, Bad), (0.0205, Average), (0.1615, Good), (0.6175, Very Good)}** |

**Table 4 – 4D:** Aggregation of Sub-Criteria for Crane Hydraulic Pump Sample 1

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_1$, $FA_H$, HR, DA | {(0.0047, Very Bad), (0.0055, Bad), (0.0123, Average), (0.0058, Good), (0.9718, Very Good)} |
| $E_2$ , $TA_1$, $FA_H$, HR, DA | {(0.0052, Very Bad), (0.0062, Bad), (0.0138, Average), (0.0750, Good), (0.8998, Very Good)} |
| $E_3$ , $TA_1$, $FA_H$, HR, DA | {(0.0052, Very Bad), (0.0062, Bad), (0.0833, Average), (0.0064, Good), (0.8989, Very Good)} |
| $E_4$ , $TA_1$, $FA_H$, HR, DA | {(0.0052, Very Bad), (0.0747, Bad), (0.0138, Average), (0.0065, Good), (0.8998, Very Good)} |
| $E_5$ , $TA_1$, $FA_H$, HR, DA | {(0.0736, Very Bad), (0.0062, Bad), (0.0138, Average), (0.0065, Good), (0.8999, Very Good)} |
| **Aggregation result (main criteria) $H_1$** | **{(0.0124, Very Bad), (0.0130, Bad), (0.0182, Average), (0.0132, Good), (0.9432, Very Good)}** |

**Table 5 – 4D:** Aggregation of Sub-Criteria for Crane Bearing Sample 2

| Sub-Criteria | Fuzzy Set | Utility Value |
|---|---|---|
| $E_1$ , $TA_2$, $FA_B$, HR, DA | {(0.0315, Very Bad), (0.0113, Bad), (0.0347, Average), (0.1275, Good), (0.7950, Very Good)} | 0.9108 |
| $E_2$ , $TA_2$, $FA_B$, HR, DA | {(0.0344, Very Bad), (0.0123, Bad), (0.0380, Average), (0.2751, Good), (0.6402, Very Good)} | 0.8686 |
| $E_3$ , $TA_2$, $FA_B$, HR, DA | {(0.0351, Very Bad), (0.0126, Bad), (0.1575, Average), (0.1422, Good), (0.6526, Very Good)} | 0.8411 |
| $E_4$ , $TA_2$, $FA_B$, HR, DA | {(0.0353, Very Bad), (0.1270, Bad), (0.0389, Average), (0.1429, Good), (0.6559, Very Good)} | 0.8143 |
| $E_5$ , $TA_2$, $FA_B$, HR, DA | {(0.1532, Very Bad), (0.0126, Bad), (0.0388, Average), (0.1423, Good), (0.6531, Very Good)} | 0.7824 |
| **Aggregation result (main criteria) $B_2$** | **{(0.0460, Very Bad), (0.0275, Bad), (0.0490, Average), (0.1395, Good), (0.7380, Very Good)}** | |

**Table 6 – 4D:** Aggregation of Sub-Criteria for Crane Clutch Sample 2

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_2$, $FA_C$, HR, DA | {(0.0045, Very Bad), (0.0054, Bad), (0.0120, Average), (0.0263, Good), (0.9518, Very Good)} |
| $E_2$ , $TA_2$, $FA_C$, HR, DA | {(0.0049, Very Bad), (0.0058, Bad), (0.0130, Average), (0.0777, Good), (0.8985, Very Good)} |
| $E_3$ , $TA_2$, $FA_C$, HR, DA | {(0.0049, Very Bad), (0.0059, Bad), (0.0607, Average), (0.0286, Good), (0.8999, Very Good)} |
| $E_4$ , $TA_2$, $FA_C$, HR, DA | {(0.0049, Very Bad), (0.0528, Bad), (0.0130, Average), (0.0286, Good), (0.9006, Very Good)} |
| $E_5$ , $TA_2$, $FA_C$, HR, DA | {(0.0518, Very Bad), (0.0059, Bad), (0.0130, Average), (0.0286, Good), (0.9006, Very Good)} |
| **Aggregation result (main criteria) $C_2$** | **{(0.0094, Very Bad), (0.0100, Bad), (0.0148, Average), (0.0254, Good), (0.9404, Very Good)}** |

**Table 7 – 4D:** Aggregation of Sub-Criteria for Crane Gearbox Sample 2

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_2$, $FA_G$, HR, DA | {(0.0416, Very Bad), (0.0360, Bad), (0.0152, Average), (0.0496, Good), (0.8576, Very Good)} |
| $E_2$ , $TA_2$, $FA_G$, HR, DA | {(0.0450, Very Bad), (0.0389, Bad), (0.0164, Average), (0.1132, Good), (0.7865, Very Good)} |
| $E_3$ , $TA_2$, $FA_G$, HR, DA | {(0.0452, Very Bad), (0.0391, Bad), (0.0721, Average), (0.0538, Good), (0.7897, Very Good)} |
| $E_4$ , $TA_2$, $FA_G$, HR, DA | {(0.0451, Very Bad), (0.0970, Bad), (0.0164, Average), (0.0537, Good), (0.7878, Very Good)} |
| $E_5$ , $TA_2$, $FA_G$, HR, DA | {(0.1037, Very Bad), (0.0390, Bad), (0.0164, Average), (0.0537, Good), (0.7872, Very Good)} |
| **Aggregation result (main criteria) $G_2$** | **{(0.0412, Very Bad), (0.0366, Bad), (0.0198, Average), (0.0478, Good), (0.8545, Very Good)}** |

**Table 8 – 4D:** Aggregation of Sub-Criteria for Crane Hydraulic Pump Sample 2

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_2$, $FA_H$, HR, DA | {(0.0047, Very Bad), (0.0056, Bad), (0.0124, Average), (0.0249, Good), (0.9523, Very Good)} |
| $E_2$ , $TA_2$, $FA_H$, HR, DA | {(0.0053, Very Bad), (0.0062, Bad), (0.0139, Average), (0.0997, Good), (0.8749, Very Good)} |
| $E_3$ , $TA_2$, $FA_H$, HR, DA | {(0.0053, Very Bad), (0.0063, Bad), (0.0840, Average), (0.0279, Good), (0.8766, Very Good)} |
| $E_4$ , $TA_2$, $FA_H$, HR, DA | {(0.0053, Very Bad), (0.0754, Bad), (0.0139, Average), (0.0279, Good), (0.8775, Very Good)} |
| $E_5$ , $TA_2$, $FA_H$, HR, DA | {(0.0743, Very Bad), (0.0063, Bad), (0.0139, Average), (0.0279, Good), (0.8776, Very Good)} |
| **Aggregation result (main criteria) $H_2$** | **{(0.0127, Very Bad), (0.0134, Bad), (0.0186, Average), (0.0283, Good), (0.9269, Very Good)}** |

**Table 9 – 4D:** Aggregation of Sub-Criteria for Crane Bearing Sample 3

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_3$, $FA_B$, HR, DA | {(0.1553, Very Bad), (0.0117, Bad), (0.0658, Average), (0.0674, Good), (0.6998, Very Good)} |
| $E_2$ , $TA_3$, $FA_B$, HR, DA | {(0.1692, Very Bad), (0.0127, Bad), (0.0717, Average), (0.1999, Good), (0.5465, Very Good)} |
| $E_3$ , $TA_3$, $FA_B$, HR, DA | {(0.1692, Very Bad), (0.0127, Bad), (0.1980, Average), (0.0734, Good), (0.5467, Very Good)} |
| $E_4$ , $TA_3$, $FA_B$, HR, DA | {(0.1711, Very Bad), (0.1293, Bad), (0.0725, Average), (0.0742, Good), (0.5528, Very Good)} |
| $E_5$ , $TA_3$, $FA_B$, HR, DA | {(0.3082, Very Bad), (0.0125, Bad), (0.0704, Average), (0.0721, Good), (0.5368, Very Good)} |
| **Aggregation result (main criteria) $B_3$** | **{(0.1754, Very Bad), (0.0296, Bad), (0.0820, Average), (0.0835, Good), (0.6294, Very Good)}** |

**Table 10 – 4D:** Aggregation of Sub-Criteria for Crane Clutch Sample 3

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_3$, $FA_C$, HR, DA | {(0.0045, Very Bad), (0.0053, Bad), (0.0119, Average), (0.0141, Good), (0.9641, Very Good)} |
| $E_2$ , $TA_3$, $FA_C$, HR, DA | {(0.0049, Very Bad), (0.0058, Bad), (0.0130, Average), (0.0630, Good), (0.9133, Very Good)} |
| $E_3$ , $TA_3$, $FA_C$, HR, DA | {(0.0049, Very Bad), (0.0058, Bad), (0.0603, Average), (0.0154, Good), (0.9136, Very Good)} |
| $E_4$ , $TA_3$, $FA_C$, HR, DA | {(0.0049, Very Bad), (0.0525, Bad), (0.0130, Average), (0.0154, Good), (0.9142, Very Good)} |
| $E_5$ , $TA_3$, $FA_C$, HR, DA | {(0.0515, Very Bad), (0.0058, Bad), (0.0130, Average), (0.0154, Good), (0.9143, Very Good)} |
| **Aggregation result (main criteria) $C_3$** | **{(0.0092, Very Bad), (0.0098, Bad), (0.0146, Average), (0.0162, Good), (0.9501, Very Good)}** |

**Table 11 – 4D:** Aggregation of Sub-Criteria for Crane Gearbox Sample 3

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_3$, $FA_G$, HR, DA | {(0.0999, Very Bad), (0.0303, Bad), (0.0489, Average), (0.0503, Good), (0.7706, Very Good)} |
| $E_2$ , $TA_3$, $FA_G$, HR, DA | {(0.1070, Very Bad), (0.0325, Bad), (0.0524, Average), (0.1152, Good), (0.6930, Very Good)} |
| $E_3$ , $TA_3$, $FA_G$, HR, DA | {(0.1070, Very Bad), (0.0325, Bad), (0.1135, Average), (0.0539, Good), (0.6931, Very Good)} |
| $E_4$ , $TA_3$, $FA_G$, HR, DA | {(0.1073, Very Bad), (0.0916, Bad), (0.0525, Average), (0.0540, Good), (0.6946, Very Good)} |
| $E_5$ , $TA_3$, $FA_G$, HR, DA | {(0.1732, Very Bad), (0.0323, Bad), (0.0521, Average), (0.0535, Good), (0.6889, Very Good)} |
| **Aggregation result (main criteria) $G_3$** | **{(0.0962, Very Bad), (0.0341, Bad), (0.0502, Average), (0.0515, Good), (0.7680, Very Good)}** |

**Table 12 – 4D:** Aggregation of Sub-Criteria for Crane Hydraulic Pump Sample 3

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_3$, $FA_H$, HR, DA | {(0.0047, Very Bad), (0.0055, Bad), (0.0123, Average), (0.0058, Good), (0.9718, Very Good)} |
| $E_2$ , $TA_3$, $FA_H$, HR, DA | {(0.0052, Very Bad), (0.0062, Bad), (0.0138, Average), (0.0750, Good), (0.8998, Very Good)} |
| $E_3$ , $TA_3$, $FA_H$, HR, DA | {(0.0052, Very Bad), (0.0062, Bad), (0.0833, Average), (0.0064, Good), (0.8989, Very Good)} |
| $E_4$ , $TA_3$, $FA_H$, HR, DA | {(0.0052, Very Bad), (0.0747, Bad), (0.0138, Average), (0.0065, Good), (0.8998, Very Good)} |
| $E_5$ , $TA_3$, $FA_H$, HR, DA | {(0.0736, Very Bad), (0.0062, Bad), (0.0138, Average), (0.0065, Good), (0.8999, Very Good)} |
| **Aggregation result (main criteria) $H_3$** | **{(0.0124, Very Bad), (0.0130, Bad), (0.0182, Average), (0.0132, Good), (0.9432, Very Good)}** |

## **Appendix 4E -** Alteration of Sample 2 Oil Condition Values due to Variation in each Sub-Criterion by 0.2

**Table 1-4E:** Aggregation of Sub-Criteria for Crane Bearing

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_2$, $FA_B$, HR, DA | {(0.2315, Very Bad), (0.0113, Bad), (0.0347, Average), (0.1275, Good), (0.5950, Very Good)} |
| $E_2$ , $TA_2$, $FA_B$, HR, DA | {(0.2344, Very Bad), (0.0123, Bad), (0.0380, Average), (0.2751, Good), (0.4402, Very Good)} |
| $E_3$ , $TA_2$, $FA_B$, HR, DA | {(0.2351, Very Bad), (0.0126, Bad), (0.1575, Average), (0.1422, Good), (0.4526, Very Good)} |
| $E_4$ , $TA_2$, $FA_B$, HR, DA | {(0.2353, Very Bad), (0.1270, Bad), (0.0389, Average), (0.1429, Good), (0.4559, Very Good)} |
| $E_5$ , $TA_2$, $FA_B$, HR, DA | {(0.3532, Very Bad), (0.0126, Bad), (0.0388, Average), (0.1423, Good), (0.4531, Very Good)} |
| **Aggregation result (main criteria) $B_2$** | **{(0.2483, Very Bad), (0.0301, Bad), (0.0536, Average), (0.1525, Good), (0.5155, Very Good)}** |

**Table 2-4E:** Aggregation of Sub-Criteria for Crane Clutch

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_2$, $FA_C$, HR, DA | {(0.2045, Very Bad), (0.0054, Bad), (0.0120, Average), (0.0263, Good), (0.7518, Very Good)} |
| $E_2$ , $TA_2$, $FA_C$, HR, DA | {(0.2049, Very Bad), (0.0058, Bad), (0.0130, Average), (0.0777, Good), (0.6985, Very Good)} |
| $E_3$ , $TA_2$, $FA_C$, HR, DA | {(0.2049, Very Bad), (0.0059, Bad), (0.0607, Average), (0.0286, Good), (0.6999, Very Good)} |
| $E_4$ , $TA_2$, $FA_C$, HR, DA | {(0.2049, Very Bad), (0.0528, Bad), (0.0130, Average), (0.0286, Good), (0.7006, Very Good)} |
| $E_5$ , $TA_2$, $FA_C$, HR, DA | {(0.2518, Very Bad), (0.0059, Bad), (0.0130, Average), (0.0286, Good), (0.7006, Very Good)} |
| **Aggregation result (main criteria) $C_2$** | **{(0.1797, Very Bad), (0.0115, Bad), (0.0170, Average), (0.0291, Good), (0.7627, Very Good)}** |

**Table 3-4E:** Aggregation of Sub-Criteria for Crane Gearbox

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_2$, $FA_G$, HR, DA | {(0.2416, Very Bad), (0.0360, Bad), (0.0152, Average), (0.0496, Good), (0.6576, Very Good)} |
| $E_2$ , $TA_2$, $FA_G$, HR, DA | {(0.2450, Very Bad), (0.0389, Bad), (0.0164, Average), (0.1132, Good), (0.5865, Very Good)} |
| $E_3$ , $TA_2$, $FA_G$, HR, DA | {(0.2452, Very Bad), (0.0391, Bad), (0.0721, Average), (0.0538, Good), (0.5897, Very Good)} |
| $E_4$ , $TA_2$, $FA_G$, HR, DA | {(0.2451, Very Bad), (0.0970, Bad), (0.0164, Average), (0.0537, Good), (0.5878, Very Good)} |
| $E_5$ , $TA_2$, $FA_G$, HR, DA | {(0.3037, Very Bad), (0.0390, Bad), (0.0164, Average), (0.0537, Good), (0.5872, Very Good)} |
| **Aggregation result (main criteria) $G_2$** | **{(0.2330, Very Bad), (0.0410, Bad), (0.0221, Average), (0.0535, Good), (0.6503, Very Good)}** |

**Table 4-4E:** Aggregation of Sub-Criteria for Crane Hydraulic Pump

| Sub-Criteria | Fuzzy Set |
|---|---|
| $E_1$ , $TA_2$, $FA_H$, HR, DA | {(0.2047, Very Bad), (0.0056, Bad), (0.0124, Average), (0.0249, Good), (0.7523, Very Good)} |
| $E_2$ , $TA_2$, $FA_H$, HR, DA | {(0.2053, Very Bad), (0.0062, Bad), (0.0139, Average), (0.0997, Good), (0.6749, Very Good)} |
| $E_3$ , $TA_2$, $FA_H$, HR, DA | {(0.2053, Very Bad), (0.0063, Bad), (0.0840, Average), (0.0279, Good), (0.6766, Very Good)} |
| $E_4$ , $TA_2$, $FA_H$, HR, DA | {(0.2053, Very Bad), (0.0754, Bad), (0.0139, Average), (0.0279, Good), (0.6775, Very Good)} |
| $E_5$ , $TA_2$, $FA_H$, HR, DA | {(0.2743, Very Bad), (0.0063, Bad), (0.0139, Average), (0.0279, Good), (0.6776, Very Good)} |
| **Aggregation result (main criteria) $H_2$** | **{(0.1863, Very Bad), (0.0153, Bad), (0.0213, Average), (0.0324, Good), (0.7447, Very Good)}** |

## **Appendix 4F -** Aggregation of the Original Values with the Alteration Values of the Main Criteria for Sample 2

**Table 1-4F:** Aggregation of $B_2$ Decrement Value with Original Values of $C_2$, $G_2$ and $H_2$

| Main Criteria | Fuzzy Set |
|---|---|
| $B_2$ (Alteration Value) | {(0.2483, Very Bad), (0.0301, Bad), (0.0536, Average), (0.1525, Good), (0.5155, Very Good)} |
| $C_2$ (Original Value) | {(0.0094, Very Bad), (0.0100, Bad), (0.0148, Average), (0.0254, Good), (0.9404, Very Good)} |
| $G_2$ (Original Value) | {(0.0412, Very Bad), (0.0366, Bad), (0.0198, Average), (0.0478, Good), (0.8545, Very Good)} |
| $H_2$ (Original Value) | {(0.0127, Very Bad), (0.0134, Bad), (0.0186, Average), (0.0283, Good), (0.9269, Very Good)} |
| **Aggregation Result ($B_2$)** | **{(0.0572, Very Bad), (0.0164, Bad), (0.0195, Average), (0.0470, Good), (0.8599, Very Good)}** |

**Table 2-4F:** Aggregation of $C_2$ Decrement Value with Original Values of $B_2$, $G_2$ and $H_2$

| Main Criteria | Fuzzy Set |
|---|---|
| $B_2$ (Original Value) | {(0.0460, Very Bad), (0.0275, Bad), (0.0490, Average), (0.1395, Good), (0.7380, Very Good)} |
| $C_2$ (Alteration Value) | {(0.1797, Very Bad), (0.0115, Bad), (0.0170, Average), (0.0291, Good), (0.7627, Very Good)} |
| $G_2$ (Original Value) | {(0.0412, Very Bad), (0.0366, Bad), (0.0198, Average), (0.0478, Good), (0.8545, Very Good)} |
| $H_2$ (Original Value) | {(0.0127, Very Bad), (0.0134, Bad), (0.0186, Average), (0.0283, Good), (0.9269, Very Good)} |
| **Aggregation Result ($C_2$)** | **{(0.0510, Very Bad), (0.0160, Bad), (0.0188, Average), (0.0446, Good), (0.8695, Very Good)}** |

**Table 3-4F:** Aggregation of $G_2$ Decrement Value with Original Values of $B_2$, $C_2$ and $H_2$

| Main Criteria | Fuzzy Set |
|---|---|
| $B_2$ (Original Value) | {(0.0460, Very Bad), (0.0275, Bad), (0.0490, Average), (0.1395, Good), (0.7380, Very Good)} |
| $C_2$ (Original Value) | {(0.0094, Very Bad), (0.0100, Bad), (0.0148, Average), (0.0254, Good), (0.9404, Very Good)} |
| $G_2$ (Alteration Value) | {(0.2330, Very Bad), (0.0410, Bad), (0.0221, Average), (0.0535, Good), (0.6503, Very Good)} |
| $H_2$ (Original Value) | {(0.0127, Very Bad), (0.0134, Bad), (0.0186, Average), (0.0283, Good), (0.9269, Very Good)} |
| **Aggregation Result ($G_2$)** | **{(0.0550, Very Bad), (0.0166, Bad), (0.0190, Average), (0.0453, Good), (0.8641, Very Good)}** |

**Table 4-4F:** Aggregation of $H_2$ Decrement Value with Original Values of $B_2$, $C_2$ and $G_2$

| Main Criteria | Fuzzy Set |
|---|---|
| $B_2$ (Original Value) | {(0.0460, Very Bad), (0.0275, Bad), (0.0490, Average), (0.1395, Good), (0.7380, Very Good)} |
| $C_2$ (Original Value) | {(0.0094, Very Bad), (0.0100, Bad), (0.0148, Average), (0.0254, Good), (0.9404, Very Good)} |
| $G_2$ (Original Value) | {(0.0412, Very Bad), (0.0366, Bad), (0.0198, Average), (0.0478, Good), (0.8545, Very Good)} |
| $H_2$ (Alteration Value) | {(0.1863, Very Bad), (0.0153, Bad), (0.0213, Average), (0.0324, Good), (0.7447, Very Good)} |
| **Aggregation result ($H_2$)** | **{(0.0517, Very Bad), (0.0161, Bad), (0.0189, Average), (0.0448, Good), (0.8686, Very Good)}** |

# Chapter 5 Appendices

## **Appendix 5A –** Development of Fuzzy Membership Functions

### 5A1 Grease Sample Elements in Port Crane bearing

Based on expert opinions, the upper limit is found and the rules are written for tin (Sn) with equal distributions, demonstrated as follows:

1. If a crane bearing grease sample laboratory test has a result of 12ppm tin (Sn) or lower, then it can be categorised as 100% very low.
2. If a crane bearing grease sample laboratory test has a result of 24ppm tin (Sn), then it can be categorised as 100% low.
3. If a crane bearing grease sample laboratory test has a result of 36ppm tin (Sn), then it can be categorised as 100% average.
4. If a crane bearing grease sample laboratory test has a result of 48ppm tin (Sn), then it can be categorised as 100% high.
5. If a crane bearing grease sample laboratory test has a result of 60ppm tin (Sn) and above, then it can be categorised as 100% very high.

Based on the stated rules, the membership functions of the tin (Sn) can be constructed as shown in Figure 1-5A1.

In a similar way, the membership functions for Nickel (Ni) and Sodium (Na) elements are constructed as shown in Figures 2-5A1 and 3-5A1.

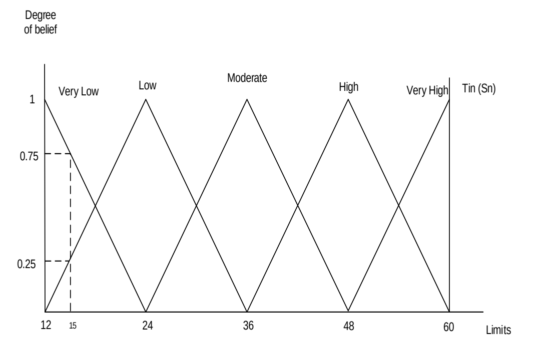

Figure 1-5A1: Membership Function of the Tin (Sn) Element

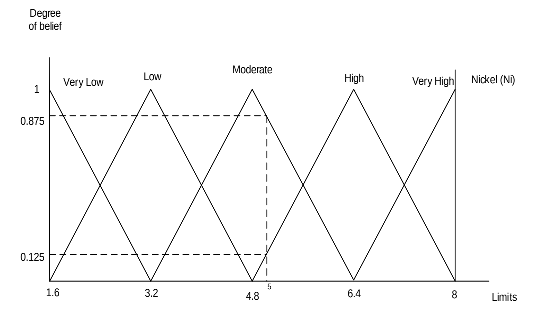

Figure 2-5A1: Membership Function of the Nickel (Ni) Element

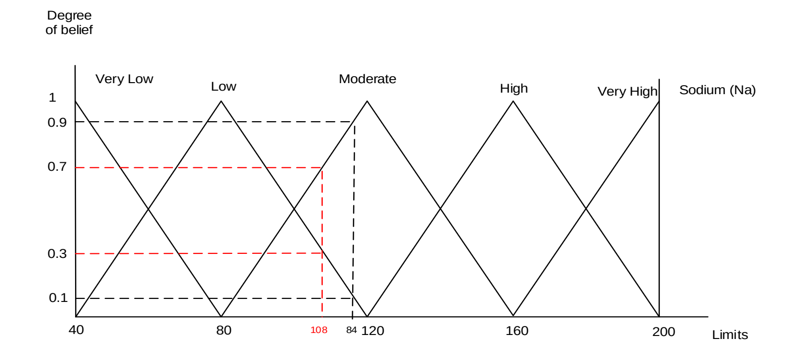


Figure 3-5A1: Membership Function of the Sodium (Na) Element

5A2 Grease Sample Elements in Starboard Crane bearing

Based on the same rules given in 5A1, the membership functions of the Nickel (Ni) and Sodium (Na) in the grease sample for starboard crane bearing can be constructed as shown in Figures 2-5A1 and 3-5A1.

5A3 Oil Sample Elements in Port Crane Gearbox

Based on expert opinions, the upper limit is found and the rules are written for tin (Sn) with equal distributions, and demonstrated as follows:

1. If a crane gearbox oil sample has a laboratory test result of 1.8ppm tin (Sn) or lower, then it can be categorised as 100% Very Low.
2. If a crane gearbox oil sample has a laboratory test result of 3.6ppm tin (Sn), then it can be categorised as 100% Low.
3. If a crane gearbox oil sample has a laboratory test result of 5.4ppm tin (Sn), then it can be categorised as 100% Average.
4. If a crane gearbox oil sample has a laboratory test result of 7.2ppm tin (Sn), then it can be categorised as 100% High.
5. If a crane gearbox oil sample has a laboratory test result of 9ppm tin (Sn) and above, then it can be categorised as 100% Very High.

Based on the stated rules, the membership functions of the tin (Sn) can be constructed as shown in Figure 1-5A3.

Based on expert opinions, the upper limit is found and the rules are written for aluminium (Al) with equal distributions, demonstrated as follows:

1. If a crane gearbox oil sample has a laboratory test result of 2ppm aluminium (Al) or lower, then it can be categorised as 100% Very Low.
2. If a crane gearbox oil sample has a laboratory test result of 4ppm aluminium (Al), then it can be categorised as 100% Low.

3. If a crane gearbox oil sample has a laboratory test result of 6ppm aluminium (Al), then it can be categorised as 100% Moderate.
4. If a crane gearbox oil sample has a laboratory test result of 8ppm aluminium (Al), then it can be categorised as 100% High.
5. If a crane gearbox oil sample has a laboratory test result of 10ppm aluminium (Al) and above, then it can be categorised as 100% Very High.

Based on the stated rules, the membership functions of the aluminium (Al) can be constructed as shown in Figure 2-5A3.

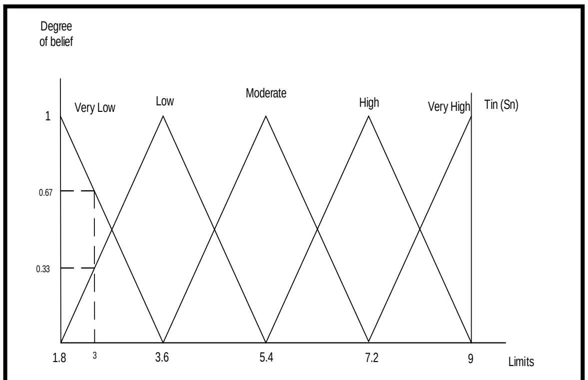

Figure 1-5A3: Membership Function of the Tin (Sn) Element

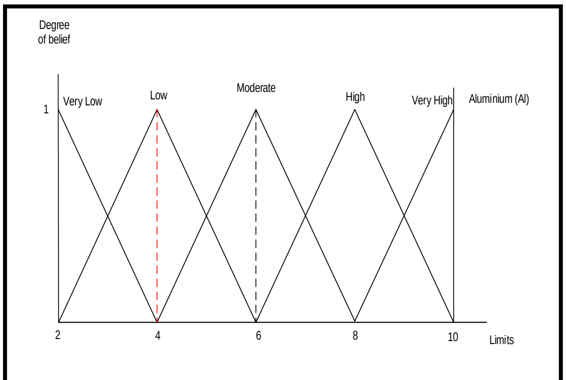

Figure 2-5A3: Membership Function of the Aluminium (Al) Element

5A4 Oil Sample Elements in Starboard Crane Gearbox

Based on the similar rules given for aluminium (Al) in 5A3, the membership functions of the aluminium (Al) for the oil sample in starboard crane gearbox can also be constructed as shown in Figure 2-5A3.

Based on expert opinions, the upper limit is found and the rules are written for silicon (Si) with equal distributions, demonstrated as follows:

1. If a crane gearbox oil sample has a laboratory test result of 8ppm silicon (Si) or lower, then it can be categorised as 100% Very Low.
2. If a crane gearbox oil sample has a laboratory test result of 16ppm silicon (Si), then it can be categorised as 100% Low.
3. If a crane gearbox oil sample has a laboratory test result of 24ppm silicon (Si), then it can be categorised as 100% Average.
4. If a crane gearbox oil sample has a laboratory test result of 32ppm silicon (Si), then it can be categorised as 100% High.
5. If a crane gearbox oil sample has a laboratory test result of 40ppm silicon (Si) and above, then it can be categorised as 100% Very High.

Based on the stated rules, the membership functions of the silicon (Si) can be constructed as shown in Figure 1-5A4.

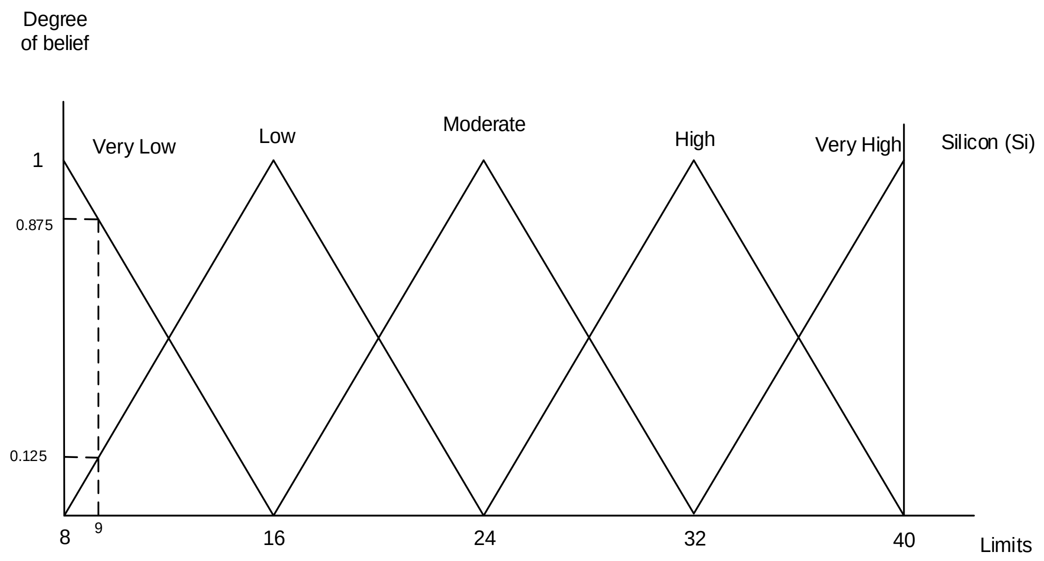


Figure 1-5A4: Membership Function of the Silicon (Si) Element

## **Appendix 5B -** Fuzzy Rule-Based Table for Risk Screening of Crane Bearing/Gearbox

**Table 1-5AB**

| Rule No. | Element A Sample Test Result | Element B Sample Test Result | Element C Sample Test Result | Priority Level of Attention |
|---|---|---|---|---|
| 1 | Very Low | Very Low | Very Low | NORMAL |
| 2 | Very Low | Very Low | Low | NORMAL |
| 3 | Very Low | Very Low | Moderate | CAUTION |
| 4 | Very Low | Very Low | High | ATTENTION |
| 5 | Very Low | Very Low | Very High | CRITICAL |
| 6 | Very Low | Low | Very Low | NORMAL |
| 7 | Very Low | Low | Low | NORMAL |
| 8 | Very Low | Low | Moderate | CAUTION |
| 9 | Very Low | Low | High | ATTENTION |
| 10 | Very Low | Low | Very High | CRITICAL |
| 11 | Very Low | Moderate | Very Low | CAUTION |
| 12 | Very Low | Moderate | Low | CAUTION |
| 13 | Very Low | Moderate | Moderate | CAUTION |
| 14 | Very Low | Moderate | High | ATTENTION |
| 15 | Very Low | Moderate | Very High | CRITICAL |
| 16 | Very Low | High | Very Low | ATTENTION |
| 17 | Very Low | High | Low | ATTENTION |
| 18 | Very Low | High | Moderate | ATTENTION |
| 19 | Very Low | High | High | ATTENTION |
| 20 | Very Low | High | Very High | CRITICAL |
| 21 | Very Low | Very High | Very Low | CRITICAL |
| 22 | Very Low | Very High | Low | CRITICAL |
| 23 | Very Low | Very High | Moderate | CRITICAL |
| 24 | Very Low | Very High | High | CRITICAL |
| 25 | Very Low | Very High | Very High | CRITICAL |
| 26 | Low | Very Low | Very Low | NORMAL |
| 27 | Low | Very Low | Low | NORMAL |
| 28 | Low | Very Low | Moderate | CAUTION |
| 29 | Low | Very Low | High | ATTENTION |
| 30 | Low | Very Low | Very High | CRITICAL |
| 31 | Low | Low | Very Low | NORMAL |
| 32 | Low | Low | Low | NORMAL |
| 33 | Low | Low | Moderate | CAUTION |
| 34 | Low | Low | High | ATTENTION |
| 35 | Low | Low | Very High | CRITICAL |
| 36 | Low | Moderate | Very Low | CAUTION |
| 37 | Low | Moderate | Low | CAUTION |
| 38 | Low | Moderate | Moderate | CAUTION |
| 39 | Low | Moderate | High | ATTENTION |
| 40 | Low | Moderate | Very High | CRITICAL |
| 41 | Low | High | Very Low | ATTENTION |

| | | | | |
|---|---|---|---|---|
| 42 | Low | High | Low | ATTENTION |
| 43 | Low | High | Moderate | ATTENTION |
| 44 | Low | High | High | ATTENTION |
| 45 | Low | High | Very High | CRITICAL |
| 46 | Low | Very High | Very Low | CRITICAL |
| 47 | Low | Very High | Low | CRITICAL |
| 48 | Low | Very High | Moderate | CRITICAL |
| 49 | Low | Very High | High | CRITICAL |
| 50 | Low | Very High | Very High | CRITICAL |
| 51 | Moderate | Very Low | Very Low | CAUTION |
| 52 | Moderate | Very Low | Low | CAUTION |
| 53 | Moderate | Very Low | Moderate | CAUTION |
| 54 | Moderate | Very Low | High | ATTENTION |
| 55 | Moderate | Very Low | Very High | CRITICAL |
| 56 | Moderate | Low | Very Low | ATTENTION |
| 57 | Moderate | Low | Low | ATTENTION |
| 58 | Moderate | Low | Moderate | ATTENTION |
| 59 | Moderate | Low | High | CAUTION |
| 60 | Moderate | Low | Very High | CRITICAL |
| 61 | Moderate | Moderate | Very Low | CAUTION |
| 62 | Moderate | Moderate | Low | CAUTION |
| 63 | Moderate | Moderate | Moderate | CAUTION |
| 64 | Moderate | Moderate | High | ATTENTION |
| 65 | Moderate | Moderate | Very High | CRITICAL |
| 66 | Moderate | High | Very Low | ATTENTION |
| 67 | Moderate | High | Low | ATTENTION |
| 68 | Moderate | High | Moderate | ATTENTION |
| 69 | Moderate | High | High | ATTENTION |
| 70 | Moderate | High | Very High | CRITICAL |
| 71 | Moderate | Very High | Very Low | CRITICAL |
| 72 | Moderate | Very High | Low | CRITICAL |
| 73 | Moderate | Very High | Moderate | CRITICAL |
| 74 | Moderate | Very High | High | CRITICAL |
| 75 | Moderate | Very High | Very High | CRITICAL |
| 76 | High | Very Low | Very Low | ATTENTION |
| 77 | High | Very Low | Low | ATTENTION |
| 78 | High | Very Low | Moderate | ATTENTION |
| 79 | High | Very Low | High | ATTENTION |
| 80 | High | Very Low | Very High | CRITICAL |
| 81 | High | Low | Very Low | ATTENTION |
| 82 | High | Low | Low | ATTENTION |
| 83 | High | Low | Moderate | ATTENTION |
| 84 | High | Low | High | ATTENTION |
| 85 | High | Low | Very High | CRITICAL |
| 86 | High | Moderate | Very Low | ATTENTION |
| 87 | High | Moderate | Low | ATTENTION |
| 88 | High | Moderate | Moderate | ATTENTION |
| 89 | High | Moderate | High | ATTENTION |
| 90 | High | Moderate | Very High | CRITICAL |
| 91 | High | High | Very Low | ATTENTION |
| 92 | High | High | Low | ATTENTION |
| 93 | High | High | Moderate | ATTENTION |
| 94 | High | High | High | ATTENTION |

| | | | | |
|---|---|---|---|---|
| 95 | High | High | Very High | CRITICAL |
| 96 | High | Very High | Very Low | CRITICAL |
| 97 | High | Very High | Low | CRITICAL |
| 98 | High | Very High | Moderate | CRITICAL |
| 99 | High | Very High | High | CRITICAL |
| 100 | High | Very High | Very High | CRITICAL |
| 101 | Very High | Very Low | Very Low | CRITICAL |
| 102 | Very High | Very Low | Low | CRITICAL |
| 103 | Very High | Very Low | Moderate | CRITICAL |
| 104 | Very High | Very Low | High | CRITICAL |
| 105 | Very High | Very Low | Very High | CRITICAL |
| 106 | Very High | Low | Very Low | CRITICAL |
| 107 | Very High | Low | Low | CRITICAL |
| 108 | Very High | Low | Moderate | CRITICAL |
| 109 | Very High | Low | High | CRITICAL |
| 110 | Very High | Low | Very High | CRITICAL |
| 111 | Very High | Moderate | Very Low | CRITICAL |
| 112 | Very High | Moderate | Low | CRITICAL |
| 113 | Very High | Moderate | Moderate | CRITICAL |
| 114 | Very High | Moderate | High | CRITICAL |
| 115 | Very High | Moderate | Very High | CRITICAL |
| 116 | Very High | High | Very Low | CRITICAL |
| 117 | Very High | High | Low | CRITICAL |
| 118 | Very High | High | Moderate | CRITICAL |
| 119 | Very High | High | High | CRITICAL |
| 120 | Very High | High | Very High | CRITICAL |
| 121 | Very High | Very High | Very Low | CRITICAL |
| 122 | Very High | Very High | Low | CRITICAL |
| 123 | Very High | Very High | Moderate | CRITICAL |
| 124 | Very High | Very High | High | CRITICAL |
| 125 | Very High | Very High | Very High | CRITICAL |

**Table 2-5B**

| Rule No. | Element A Sample Test Result | Element B Sample Test Result | Priority Level of Attention |
|---|---|---|---|
| 1 | Very Low | Very Low | NORMAL |
| 2 | Very Low | Low | NORMAL |
| 3 | Very Low | Moderate | CAUTION |
| 4 | Very Low | High | ATTENTION |
| 5 | Very Low | Very High | CRITICAL |
| 6 | Low | Very Low | NORMAL |
| 7 | Low | Low | NORMAL |
| 8 | Low | Moderate | CAUTION |
| 9 | Low | High | ATTENTION |
| 10 | Low | Very High | CRITICAL |
| 11 | Moderate | Very Low | CAUTION |
| 12 | Moderate | Low | CAUTION |
| 13 | Moderate | Moderate | CAUTION |
| 14 | Moderate | High | ATTENTION |
| 15 | Moderate | Very High | CRITICAL |
| 16 | High | Very Low | ATTENTION |
| 17 | High | Low | ATTENTION |
| 18 | High | Moderate | ATTENTION |
| 19 | High | High | ATTENTION |
| 20 | High | Very High | CRITICAL |
| 21 | Very High | Very Low | CRITICAL |
| 22 | Very High | Low | CRITICAL |
| 23 | Very High | Moderate | CRITICAL |
| 24 | Very High | High | CRITICAL |
| 25 | Very High | Very High | CRITICAL |

# **Appendix 5C -** Risk Level Determination for Decrement by 0.1

5C1 Risk level for port crane bearing grease sample test elements (Decrement of 0.1)

By applying the 'min-max' approach, the set of fuzzy conclusions of the port crane bearing grease sample test element in Table 5.24 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Sn = Very Low 0.65, Ni = Moderate 0.775, and Na = Low 0.8, then based on rule 12 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(2) If Sn = Very Low 0.65, Ni = Moderate 0.775, and Na = Moderate 0.1, then based on rule 13 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(3) If Sn = Very Low 0.65, Ni = Moderate 0.775, and Na = Very High 0.1, then based on rule 15 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(4) If Sn = Very Low 0.65, Ni = High 0.125, and Na = Low 0.8, then based on rule 17 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(5) If Sn = Very Low 0.65, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 18 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(6) If Sn = Very Low 0.65, Ni = High 0.125, and Na = Very High 0.1, then based on rule 20 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(7) If Sn = Very Low 0.65, Ni = Very High 0.1, and Na = Low 0.8, then based on rule 22 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(8) If Sn = Very Low 0.65, Ni = Very High 0.1, and Na = Moderate 0.1, then based on rule 23 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(9) If Sn = Very Low 0.65, Ni = Very High 0.1, and Na = Very High 0.1, then based on rule 25 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(10) If Sn = Low 0.25, Ni = Moderate 0.775, and Na = Low 0.8, then based on rule 37 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(11) If Sn = Low 0.25, Ni = Moderate 0.775, and Na = Moderate 0.1, then based on rule 38 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(12) If Sn = Low 0.25, Ni = Moderate 0.775, and Na = Very High 0.1, then based on rule 40 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(13) If Sn = Low 0.25, Ni = High 0.125, and Na = Low 0.8, then based on rule 42 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(14) If Sn = Low 0.25, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 43 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(15) If Sn = Low 0.25, Ni = High 0.125, and Na = Very High 0.1, then based on rule 45 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(16) If Sn = Low 0.25, Ni = Very High 0.1, and Na = Low 0.8, then based on rule 47 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(17) If Sn = Low 0.25, Ni = Very High 0.1, and Na = Moderate 0.1, then based on rule 48 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(18) If Sn = Low 0.25, Ni = Very High 0.1, and Na = Very High 0.1, then based on rule 50 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(19) If Sn = Very High 0.1, Ni = Moderate 0.775, and Na = Low 0.8, then based on rule 112 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(20) If Sn = Very High 0.1, Ni = Moderate 0.775, and Na = Moderate 0.1, then based on rule 113 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(21) If Sn = Very High 0.1, Ni = Moderate 0.775, and Na = Very High 0.1, then based on rule 115 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(22) If Sn = Very High 0.1, Ni = High 0.125, and Na = Low 0.8, then based on rule 117 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(23) If Sn = Very High 0.1, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 118 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(24) If Sn = Very High 0.1, Ni = High 0.125, and Na = Very High 0.1, then based on rule 120 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(25) If Sn = Very High 0.1, Ni = Very High 0.1, and Na = Low 0.8, then based on rule 122 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(26) If Sn = Very High 0.1, Ni = Very High 0.1, and Na = Moderate 0.1, then based on rule 123 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(27) If Sn = Very High 0.1, Ni = Very High 0.1, and Na = Very High 0.1, then based on rule 125 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.65, Ni = Moderate 0.775, and Na = Low 0.8. Therefore, the minimum value of Sn, Ni and Na is 0.65, which is associated with the linguistic priority term CAUTION according to the fuzzy rule developed. The minimum values of the other twenty-six combinations can be determined in a similar way as shown in Table 1-5C.

**Table 1-5C:** The Minimum Value of each Combination for Port Crane Bearing

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | Caution 0.65 | 2 | Caution 0.1 | 3 | Critical 0.1 | 4 | Attention 0.125 |
| 5 | Attention 0.1 | 6 | Critical 0.1 | 7 | Critical 0.1 | 8 | Critical 0.1 |
| 9 | Critical 0.1 | 10 | Caution 0.25 | 11 | Caution 0.1 | 12 | Critical 0.1 |
| 13 | Attention 0.125 | 14 | Attention 0.1 | 15 | Critical 0.1 | 16 | Critical 0.1 |
| 17 | Critical 0.1 | 18 | Critical 0.1 | 19 | Critical 0.1 | 20 | Critical 0.1 |
| 21 | Critical 0.1 | 22 | Critical 0.1 | 23 | Critical 0.1 | 24 | Critical 0.1 |
| 25 | Critical 0.1 | 26 | Critical 0.1 | 27 | Critical 0.1 | | |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are twenty-seven combinations and three different categories of linguistic priority terms, CAUTION, ATTENTION and CRITICAL. The membership values in

the CAUTION category are 0.65, 0.1, 0.25 and 0.1, respectively. Therefore, the maximum membership value is 0.65 as shown in Table 2-5C. Likewise, the maximum membership values in the ATTENTION and CRITICAL categories are determined as shown in Table 2-5C.

**Table 2-5C:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Caution | 0.65 |
| Attention | 0.125 |
| Critical | 0.1 |

5C2 Risk Level for Starboard Crane Bearing Grease Sample Test Elements

By applying the 'min-max' approach, the set of fuzzy conclusions of the starboard crane bearing grease sample test element in Table 5.25 of Chapter 5 is obtained as follows:

iii. List the membership function values according to the rules developed.

(3) If Ni = Very Low 0.1, and Na = Low 0.2, then based on rule 2 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.

(4) If Ni = Very Low 0.1, and Na = Moderate 0.7, then based on rule 3 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

(5) If Ni = Very Low 0.1, and Na = Very High 0.1, then based on rule 5 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(6) If Ni = Very High 0.9, and Na = Low 0.2, then based on rule 22 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(7) If Ni = Very High 0.9, and Na = Moderate 0.7, then based on rule 23 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(8) If Ni = Very High 0.9, and Na = Very High 0.1, then based on rule 25 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

iv. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Ni = Very Low 0.1 and Na = Low 0.2. Therefore, the minimum value of Ni and Na is 0.1, which is associated with the linguistic priority term NORMAL according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 3-5C.

**Table 3-5C:** The Minimum Value of each Combination for Starboard Crane Bearing

| | | | | | |
|---|---|---|---|---|---|
| 1 | Normal 0.1 | 2 | Caution 0.1 | 3 | Critical 0.1 |
| 4 | Critical 0.2 | 5 | Critical 0.7 | 6 | Critical 0.1 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority terms.

In the first scenario, there are six combinations and three categories of linguistic priority terms, NORMAL, CAUTION and CRITICAL. The membership values in the NORMAL category is 0.1. Therefore, the maximum membership value is 0.1 as shown in Table 4-5C. Likewise, the maximum membership values in the CAUTION and CRITICAL categories are determined as shown in Table 4-5C.

**Table 4-5C:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Starboard Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Normal | 0.1 |
| Caution | 0.1 |
| Critical | 0.7 |

5C3 Risk Level for Port Crane Gearbox Oil Sample Test Elements (Decrement of 0.1)

By applying the 'min-max' approach, the set of fuzzy conclusions of port crane gearbox oil sample test element in Table 5.26 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Sn = Very Low 0.233, and Al = Low 0.9, then based on rule 2 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.

(2) If Sn = Very Low 0.233, and Al = Very High 0.1, then based on rule 5 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(3) If Sn = Low 0.667, and Al = Low 0.9, then based on rule 7 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.

(4) If Sn = Low 0.667, and Al = Very High 0.1, then based on rule 10 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(5) If Sn = Very High 0.1, and Al = Low 0.9, then based on rule 22 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(6) If Sn = Very High 0.1, and Al = Very High 0.1, then based on rule 25 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.233, and Al = Low 0.9. Therefore, the minimum value of Sn and Al is 0.233, which is associated with the linguistic priority term NORMAL according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 5-5C.

**Table 5-5C:** The Minimum Value of each Combination for Port Crane Gearbox

| | | | | | |
|---|---|---|---|---|---|
| 1 | Normal 0.233 | 2 | Critical 0.1 | 3 | Normal 0.667 |
| 4 | Critical 0.1 | 5 | Critical 0.1 | 6 | Critical 0.1 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are six combinations and two categories of linguistic priority terms, NORMAL and CRITICAL. The membership values in the NORMAL category are 0.233 and 0.667. Therefore, the maximum membership value is 0.667. Likewise, the maximum membership value in the CRITICAL category is determined as shown in Table 6-5C.

**Table 6-5C:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Gearbox.

| **Category of linguistic priority terms** | **Maximum values** |
|---|---|
| Normal | 0.667 |
| Critical | 0.1 |

5C4 Risk Level for Starboard Crane Gearbox Oil Sample Test Elements (Decrement of 0.1)

By applying the 'min-max' approach, the set of fuzzy conclusions of starboard crane gearbox oil sample test element in Table 5.27 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Al = Moderate 0.9, and Si = Very Low 0.775, then based on rule 11 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

(2) If Al = Moderate 0.9, and Si = Low 0.125, then based on rule 12 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

(3) If Al = Moderate 0.9, and Si = Very High 0.1, then based on rule 15 on the fuzzy rule based table (Table 2-4A in Appendix 4A), the priority level is CRITICAL.

(4) If Al = Very High 0.1, and Si = Very Low 0.775, then based on rule 21 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(5) If Al = Very High 0.1, and Si = Low 0.125, then based on rule 22 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(6) If Al = Very High 0.1, and Si = Very High 0.1, then based on rule 25 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Al = Moderate 0.9, and Si = Very Low 0.775. Therefore, the minimum value of Al and Si is 0.775, which is associated with the linguistic priority term CAUTION according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 7-5C.

**Table 7-5C:** The Minimum Value of each Combination for Starboard Crane Gearbox

| | | | | | |
|---|---|---|---|---|---|
| 1 | Caution 0.775 | 2 | Caution 0.125 | 3 | Critical 0.1 |
| 4 | Critical 0.1 | 5 | Critical 0.1 | 6 | Critical 0.1 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are six combinations and two categories of linguistic priority terms, CAUTION and CRITICAL. The membership values in the CAUTION category are 0.775 and 0.125. Therefore, the maximum membership value is 0.775. Likewise, the maximum membership value in the CRITICAL category is determined as shown in Table 8-5C.

**Table 8-5C:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Starboard Crane Gearbox.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Caution | 0.775 |
| Critical | 0.1 |

## **Appendix 5D -** Risk Level Determination for Decrement by 0.2

5D1 Risk level for port crane bearing grease sample test elements (0.2 decrement)

By applying the ‘min-max’ approach, the set of fuzzy conclusions of the port crane bearing grease sample test element in Table 5.28 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Sn = Very Low 0.55, Ni = Moderate 0.675, and Na = Low 0.7, then based on rule 12 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(2) If Sn = Very Low 0.55, Ni = Moderate 0.675, and Na = Moderate 0.1, then based on rule 13 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(3) If Sn = Very Low 0.55, Ni = Moderate 0.675, and Na = Very High 0.2, then based on rule 15 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(4) If Sn = Very Low 0.55, Ni = High 0.125, and Na = Low 0.7, then based on rule 17 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(5) If Sn = Very Low 0.55, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 18 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(6) If Sn = Very Low 0.55, Ni = High 0.125, and Na = Very High 0.2, then based on rule 20 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(7) If Sn = Very Low 0.55, Ni = Very High 0.2, and Na = Low 0.7, then based on rule 22 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(8) If Sn = Very Low 0.55, Ni = Very High 0.2, and Na = Moderate 0.1, then based on rule 23 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(9) If Sn = Very Low 0.55, Ni = Very High 0.2, and Na = Very High 0.2, then based on rule 25 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(10) If Sn = Low 0.25, Ni = Moderate 0.675, and Na = Low 0.7, then based on rule 37 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(11) If Sn = Low 0.25, Ni = Moderate 0.675, and Na = Moderate 0.1, then based on rule 38 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(12) If Sn = Low 0.25, Ni = Moderate 0.675, and Na = Very High 0.2, then based on rule 40 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(13) If Sn = Low 0.25, Ni = High 0.125, and Na = Low 0.7, then based on rule 42 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(14) If Sn = Low 0.25, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 43 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(15) If Sn = Low 0.25, Ni = High 0.125, and Na = Very High 0.2, then based on rule 45 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(16) If Sn = Low 0.25, Ni = Very High 0.2, and Na = Low 0.7, then based on rule 47 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(17) If Sn = Low 0.25, Ni = Very High 0.2, and Na = Moderate 0.1, then based on rule 48 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(18) If Sn = Low 0.25, Ni = Very High 0.2, and Na = Very High 0.2, then based on rule 50 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(19) If Sn = Very High 0.2, Ni = Moderate 0.675, and Na = Low 0.7, then based on rule 112 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(20) If Sn = Very High 0.2, Ni = Moderate 0.675, and Na = Moderate 0.1, then based on rule 113 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(21) If Sn = Very High 0.2, Ni = Moderate 0.675, and Na = Very High 0.2, then based on rule 115 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(22) If Sn = Very High 0.2, Ni = High 0.125, and Na = Low 0.7, then based on rule 117 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(23) If Sn = Very High 0.2, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 118 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(24) If Sn = Very High 0.2, Ni = High 0.125, and Na = Very High 0.2, then based on rule 120 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(25) If Sn = Very High 0.2, Ni = Very High 0.2, and Na = Low 0.7, then based on rule 122 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(26) If Sn = Very High 0.2, Ni = Very High 0.2, and Na = Moderate 0.1, then based on rule 123 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(27) If Sn = Very High 0.2, Ni = Very High 0.2, and Na = Very High 0.2, then based on rule 125 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.55, Ni = Moderate 0.675, and Na = Low 0.7. Therefore, the minimum value of Sn, Ni and Na is 0.55, which is associated with the linguistic priority term CAUTION according to the fuzzy rule developed. The minimum values of the other twenty-six combinations can be determined in a similar way as shown in Table 1-5D.

**Table 1-5D:** The Minimum Value of each Combination for Port Crane Bearing

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | Caution 0.55 | 2 | Caution 0.1 | 3 | Critical 0.2 | 4 | Attention 0.125 |
| 5 | Attention 0.1 | 6 | Critical 0.125 | 7 | Critical 0.2 | 8 | Critical 0.1 |
| 9 | Critical 0.2 | 10 | Caution 0.25 | 11 | Caution 0.1 | 12 | Critical 0.2 |
| 13 | Attention 0.125 | 14 | Attention 0.1 | 15 | Critical 0.125 | 16 | Critical 0.2 |
| 17 | Critical 0.1 | 18 | Critical 0.2 | 19 | Critical 0.2 | 20 | Critical 0.1 |
| 21 | Critical 0.2 | 22 | Critical 0.125 | 23 | Critical 0.1 | 24 | Critical 0.125 |
| 25 | Critical 0.2 | 26 | Critical 0.1 | 27 | Critical 0.2 | | |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are twenty-seven combinations and three different categories of linguistic priority terms, CAUTION, ATTENTION and CRITICAL. The membership values in

the CAUTION category are 0.55, 0.1, 0.25 and 0.1, respectively. Therefore, the maximum membership value is 0.55 as shown in Table 2-5D. Likewise, the maximum membership values in the ATTENTION and CRITICAL categories are determined as shown in Table 2-5D.

**Table 2-5D:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Caution | 0.55 |
| Attention | 0.125 |
| Critical | 0.2 |

5D2 Risk Level for Starboard Crane Bearing Grease Sample Test Elements (0.2 decrement).

By applying the 'min-max' approach, the set of fuzzy conclusions of the starboard crane bearing grease sample test element in Table 5.29 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Ni = Very Low 0.2, and Na = Low 0.1, then based on rule 2 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.
   (2) If Ni = Very Low 0.2, and Na = Moderate 0.7, then based on rule 3 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.
   (3) If Ni = Very Low 0.2, and Na = Very High 0.2, then based on rule 5 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (4) If Ni = Very High 0.8, and Na = Low 0.1, then based on rule 22 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (5) If Ni = Very High 0.8, and Na = Moderate 0.7, then based on rule 23 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (6) If Ni = Very High 0.8, and Na = Very High 0.2, then based on rule 25 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Ni = Very Low 0.2 and Na = Low 0.1. Therefore, the minimum value of Ni and Na is 0.1, which is associated with the linguistic priority term NORMAL according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 3-5D.

**Table 3-5D:** The Minimum Value of each Combination for Starboard Crane Bearing

| | | | | | |
|---|---|---|---|---|---|
| 1 | Normal 0.1 | 2 | Caution 0.2 | 3 | Critical 0.2 |
| 4 | Critical 0.1 | 5 | Critical 0.7 | 6 | Critical 0.2 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority terms.

In the first scenario, there are six combinations and three categories of linguistic priority terms, NORMAL, CAUTION and CRITICAL. The membership values in the NORMAL category is 0.1. Therefore, the maximum membership value is 0.1 as shown in Table 4-5D. Likewise, the maximum membership values in the CAUTION and CRITICAL categories are determined as shown in Table 4-5D.

**Table 4-5D:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Starboard Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Normal | 0.1 |
| Caution | 0.2 |
| Critical | 0.7 |

5D3 Risk Level for Port Crane Gearbox Oil Sample Test Elements (0.2 decrement)

By applying the ‘min-max’ approach, the set of fuzzy conclusions of port crane gearbox oil sample test element in Table 5.30 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Sn = Very Low 0.133, and Al = Low 0.8, then based on rule 2 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.
   (2) If Sn = Very Low 0.133, and Al = Very High 0.2, then based on rule 5 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (3) If Sn = Low 0.667, and Al = Low 0.8, then based on rule 7 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.
   (4) If Sn = Low 0.667, and Al = Very High 0.2, then based on rule 10 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (5) If Sn = Very High 0.2, and Al = Low 0.8, then based on rule 22 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(6) If Sn = Very High 0.2, and Al = Very High 0.2, then based on rule 25 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.133, and Al = Low 0.8. Therefore, the minimum value of Sn and Al is 0.133, which is associated with the linguistic priority term NORMAL according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 5-5D.

**Table 5-5D:** The Minimum Value of each Combination for Port Crane Gearbox

| | | | | | |
|---|---|---|---|---|---|
| 1 | Normal 0.133 | 2 | Critical 0.133 | 3 | Normal 0.667 |
| 4 | Critical 0.2 | 5 | Critical 0.2 | 6 | Critical 0.2 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are six combinations and two categories of linguistic priority terms, NORMAL and CRITICAL. The membership values in the NORMAL category are 0.133 and 0.667. Therefore, the maximum membership value is 0.667. Likewise, the maximum membership value in the CRITICAL category is determined as shown in Table 6-5D.

**Table 6-5D:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Gearbox.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Normal | 0.667 |
| Critical | 0.2 |

5D4 Risk Level for Starboard Crane Gearbox Oil Sample Test Elements (0.2 decrement)

By applying the ‘min-max’ approach, the set of fuzzy conclusions of starboard crane gearbox oil sample test element in Table 5.31 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Al = Moderate 0.8, and Si = Very Low 0.675, then based on rule 11 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

(2) If Al = Moderate 0.8, and Si = Low 0.125, then based on rule 12 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

(3) If Al = Moderate 0.8, and Si = Very High 0.2, then based on rule 15 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(4) If AI = Very High 0.2, and Si = Very Low 0.675, then based on rule 21 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(5) If AI = Very High 0.2, and Si = Low 0.125, then based on rule 22 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(6) If AI = Very High 0.2, and Si = Very High 0.2, then based on rule 25 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), AI = Moderate 0.8, and Si = Very Low 0.675. Therefore, the minimum value of AI and Si is 0.675, which is associated with the linguistic priority term CAUTION according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 7-5D.

**Table 7-5D:** The Minimum Value of each Combination for Starboard Crane Gearbox

| | | | | | |
|---|---|---|---|---|---|
| 1 | Caution 0.675 | 2 | Caution 0.125 | 3 | Critical 0.2 |
| 4 | Critical 0.2 | 5 | Critical 0.125 | 6 | Critical 0.2 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are six combinations and two categories of linguistic priority terms, CAUTION and CRITICAL. The membership values in the CAUTION category are 0.675 and 0.125. Therefore, the maximum membership value is 0.675. Likewise, the maximum membership value in the CRITICAL category is determined as shown in Table 8-5D.

**Table 8-5D:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Starboard Crane Gearbox.

| **Category of linguistic priority terms** | **Maximum values** |
|---|---|
| Caution | 0.675 |
| Critical | 0.2 |

## **Appendix 5E -** Risk Level Determination for Decrement by 0.3

5E1 Risk level for port crane bearing grease sample test elements (0.3 decrement)

By applying the 'min-max' approach, the set of fuzzy conclusions of the port crane bearing grease sample test element in Table 5.32 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Sn = Very Low 0.45, Ni = Moderate 0.575, and Na = Low 0.6, then based on rule 12 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(2) If Sn = Very Low 0.45, Ni = Moderate 0.575, and Na = Moderate 0.1, then based on rule 13 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(3) If Sn = Very Low 0.45, Ni = Moderate 0.575, and Na = Very High 0.3, then based on rule 15 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(4) If Sn = Very Low 0.45, Ni = High 0.125, and Na = Low 0.6, then based on rule 17 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(5) If Sn = Very Low 0.45, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 18 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(6) If Sn = Very Low 0.45, Ni = High 0.125, and Na = Very High 0.3, then based on rule 20 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(7) If Sn = Very Low 0.45, Ni = Very High 0.3, and Na = Low 0.6, then based on rule 22 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(8) If Sn = Very Low 0.45, Ni = Very High 0.3, and Na = Moderate 0.1, then based on rule 23 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(9) If Sn = Very Low 0.45, Ni = Very High 0.3, and Na = Very High 0.3, then based on rule 25 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(10) If Sn = Low 0.25, Ni = Moderate 0.575, and Na = Low 0.6, then based on rule 37 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(11) If Sn = Low 0.25, Ni = Moderate 0.575, and Na = Moderate 0.1, then based on rule 38 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CAUTION.

(12) If Sn = Low 0.25, Ni = Moderate 0.575, and Na = Very High 0.3, then based on rule 40 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(13) If Sn = Low 0.25, Ni = High 0.125, and Na = Low 0.6, then based on rule 42 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(14) If Sn = Low 0.25, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 43 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is ATTENTION.

(15) If Sn = Low 0.25, Ni = High 0.125, and Na = Very High 0.3, then based on rule 45 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(16) If Sn = Low 0.25, Ni = Very High 0.3, and Na = Low 0.6, then based on rule 47 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(17) If Sn = Low 0.25, Ni = Very High 0.3, and Na = Moderate 0.1, then based on rule 48 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(18) If Sn = Low 0.25, Ni = Very High 0.3, and Na = Very High 0.3, then based on rule 50 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(19) If Sn = Very High 0.3, Ni = Moderate 0.575, and Na = Low 0.6, then based on rule 112 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(20) If Sn = Very High 0.3, Ni = Moderate 0.575, and Na = Moderate 0.1, then based on rule 113 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(21) If Sn = Very High 0.3, Ni = Moderate 0.575, and Na = Very High 0.3, then based on rule 115 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(22) If Sn = Very High 0.3, Ni = High 0.125, and Na = Low 0.6, then based on rule 117 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(23) If Sn = Very High 0.3, Ni = High 0.125, and Na = Moderate 0.1, then based on rule 118 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(24) If Sn = Very High 0.3, Ni = High 0.125, and Na = Very High 0.3, then based on rule 120 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(25) If Sn = Very High 0.3, Ni = Very High 0.3, and Na = Low 0.6, then based on rule 122 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(26) If Sn = Very High 0.3, Ni = Very High 0.3, and Na = Moderate 0.1, then based on rule 123 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

(27) If Sn = Very High 0.3, Ni = Very High 0.3, and Na = Very High 0.3, then based on rule 125 in the fuzzy rule based table (Table 1-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.45, Ni = Moderate 0.575, and Na = Low 0.6. Therefore, the minimum value of Sn, Ni and Na is 0.45, which is associated with the linguistic priority term CAUTION according to the fuzzy rule developed. The minimum values of the other twenty-six combinations can be determined in a similar way as shown in Table 1-5E.

**Table 1-5E:** The Minimum Value of each Combination for Port Crane Bearing

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | Caution 0.45 | 2 | Caution 0.1 | 3 | Critical 0.3 | 4 | Attention 0.125 |
| 5 | Attention 0.1 | 6 | Critical 0.125 | 7 | Critical 0.3 | 8 | Critical 0.1 |
| 9 | Critical 0.3 | 10 | Caution 0.25 | 11 | Caution 0.1 | 12 | Critical 0.25 |
| 13 | Attention 0.125 | 14 | Attention 0.1 | 15 | Critical 0.125 | 16 | Critical 0.25 |
| 17 | Critical 0.1 | 18 | Critical 0.25 | 19 | Critical 0.3 | 20 | Critical 0.1 |
| 21 | Critical 0.3 | 22 | Critical 0.125 | 23 | Critical 0.1 | 24 | Critical 0.125 |
| 25 | Critical 0.3 | 26 | Critical 0.1 | 27 | Critical 0.3 | | |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are twenty-seven combinations and three different categories of linguistic priority terms, CAUTION, ATTENTION and CRITICAL. The membership values in

the CAUTION category are 0.45, 0.1, 0.25 and 0.1, respectively. Therefore, the maximum membership value is 0.45 as shown in Table 2-5E. Likewise, the maximum membership values in the ATTENTION and CRITICAL categories are determined as shown in Table 2-4D.

**Table 2-5E:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Caution | 0.45 |
| Attention | 0.125 |
| Critical | 0.3 |

5E2 Risk Level for Starboard Crane Bearing Grease Sample Test Elements (0.3 decrement)

By applying the 'min-max' approach, the set of fuzzy conclusions of the starboard crane bearing grease sample test element in Table 5.33 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Ni = Very Low 0.3, and Na = Moderate 0.7, then based on rule 3 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.
   (2) If Ni = Very Low 0.3, and Na = Very High 0.3, then based on rule 5 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (3) If Ni = Very High 0.7, and Na = Moderate 0.7, then based on rule 23 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (4) If Ni = Very High 0.7, and Na = Very High 0.3, then based on rule 25 in the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Ni = Very Low 0.3 and Na = Moderate 0.7. Therefore, the minimum value of Ni and Na is 0.3, which is associated with the linguistic priority term CAUTION according to the fuzzy rule developed. The minimum values of the other three combinations can be determined in a similar way as shown in Table 3-5E.

**Table 3-5E:** The Minimum Value of each Combination for Starboard Crane Bearing

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | Caution 0.3 | 2 | Critical 0.3 | 3 | Critical 0.7 | 4 | Critical 0.3 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority terms.

In the first scenario, there are four combinations and two categories of linguistic priority terms, CAUTION and CRITICAL. The membership values in the CAUTION category is 0.3. Therefore, the maximum membership value is 0.3 as shown in Table 4-5E. Likewise, the maximum membership value in the CRITICAL category is determined as shown in Table 4-5E.

**Table 4-5E:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Starboard Crane Bearing.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Caution | 0.3 |
| Critical | 0.7 |

5E3 Risk Level for Port Crane Gearbox Oil Sample Test Elements (0.3 decrement)

By applying the 'min-max' approach, the set of fuzzy conclusions of port crane gearbox oil sample test element in Table 5.34 of Chapter 5 is obtained as follows:

i. List the membership function values according to the rules developed.
   (1) If Sn = Very Low 0.033, and Al = Low 0.7, then based on rule 2 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.
   (2) If Sn = Very Low 0.033, and Al = Very High 0.3, then based on rule 5 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (3) If Sn = Low 0.667, and Al = Low 0.7, then based on rule 7 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is NORMAL.
   (4) If Sn = Low 0.667, and Al = Very High 0.3, then based on rule 10 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (5) If Sn = Very High 0.3, and Al = Low 0.7, then based on rule 22 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.
   (6) If Sn = Very High 0.3, and Al = Very High 0.3, then based on rule 25 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), Sn = Very Low 0.033, and Al = Low 0.7. Therefore, the minimum value of Sn and Al is 0.033, which is associated with the linguistic priority term

NORMAL according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 5-5E.

**Table 5-5E:** The Minimum Value of each Combination for Port Crane Gearbox

| | | | | | |
|---|---|---|---|---|---|
| 1 | Normal 0.033 | 2 | Critical 0.033 | 3 | Normal 0.667 |
| 4 | Critical 0.3 | 5 | Critical 0.3 | 6 | Critical 0.3 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are six combinations and two categories of linguistic priority terms, NORMAL and CRITICAL. The membership values in the NORMAL category are 0.033 and 0.667. Therefore, the maximum membership value is 0.667. Likewise, the maximum membership value in the CRITICAL category is determined as shown in Table 6-5E.

**Table 6-5E:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Port Crane Gearbox.

| **Category of linguistic priority terms** | **Maximum values** |
|---|---|
| Normal | 0.667 |
| Critical | 0.3 |

5E4 Risk Level for Starboard Crane Gearbox Oil Sample Test Elements (0.3 decrement)

By applying the ‘min-max’ approach, the set of fuzzy conclusions of starboard crane gearbox oil sample test element in Table 5.35 is obtained as follows:

i. List the membership function values according to the rules developed.

(1) If Al = Moderate 0.7, and Si = Very Low 0.575, then based on rule 11 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

(2) If Al = Moderate 0.7, and Si = Low 0.125, then based on rule 12 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CAUTION.

(3) If Al = Moderate 0.7, and Si = Very High 0.3, then based on rule 15 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(4) If Al = Very High 0.3, and Si = Very Low 0.575, then based on rule 21 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(5) If Al = Very High 0.3, and Si = Low 0.125, then based on rule 22 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

(6) If AI = Very High 0.3, and Si = Very High 0.3, then based on rule 25 on the fuzzy rule based table (Table 2-5B in Appendix 5B), the priority level is CRITICAL.

ii. Determine the minimum value of each combination in terms of comparing the values obtained from each element and the value of weight established in the priority level.

In the first combination in (i), AI = Moderate 0.7, and Si = Very Low 0.575. Therefore, the minimum value of AI and Si is 0.575, which is associated with the linguistic priority term CAUTION according to the fuzzy rule developed. The minimum values of the other five combinations can be determined in a similar way as shown in Table 7-5E.

**Table 7-5E:** The Minimum Value of each Combination for Starboard Crane Gearbox

| | | | | | |
|---|---|---|---|---|---|
| 1 | Caution 0.575 | 2 | Caution 0.125 | 3 | Critical 0.3 |
| 4 | Critical 0.3 | 5 | Critical 0.125 | 6 | Critical 0.3 |

iii. Determine the maximum value of the minimum values obtained from step 2 that have the same category of linguistic priority term.

In the first scenario, there are six combinations and two categories of linguistic priority terms, CAUTION and CRITICAL. The membership values in the CAUTION category are 0.575 and 0.125. Therefore, the maximum membership value is 0.575. Likewise, the maximum membership value in the CRITICAL category is determined as shown in Table 8-5E.

**Table 8-5E:** The Maximum Value Associated with the Same Category of Linguistic Priority Terms for Starboard Crane Gearbox.

| Category of linguistic priority terms | Maximum values |
|---|---|
| Caution | 0.575 |
| Critical | 0.3 |

## **Appendix 5F -** Risk Values for Decremented Set of Fuzzy Conclusions

Using the defuzzification process described in Section 5.46, and the decrement set of fuzzy conclusions shown in Table 5.40 in Chapter 5, the risk (utility) values can be calculated as follows:

**Port Crane Bearing**

10% decrement:

$$Caution\ \frac{0.65}{0.65+0.125+0.1},\ Attention\ \frac{0.125}{0.65+0.125+0.1},\ Critical\ \frac{0.1}{0.65+0.125+0.1}$$

$$RV = 2\ \times\ \frac{0.65}{0.65+0.125+0.1} + 3\ \times\ \frac{0.125}{0.65+0.125+0.1} + 4\ \times\ \frac{0.1}{0.65+0.125+0.1}\ = 2.366$$

20% decrement:

$$Caution\ \frac{0.55}{0.55+0.125+0.2},\ Attention\ \frac{0.125}{0.55+0.125+0.2},\ Critical\ \frac{0.2}{0.55+0.125+0.2}$$

$$RV = 2\ \times\ \frac{0.55}{0.55+0.125+0.2} + 3\ \times\ \frac{0.125}{0.55+0.125+0.2} + 4\ \times\ \frac{0.2}{0.55+0.125+0.2}\ = 2.594$$

30% decrement:

$$Caution\ \frac{0.45}{0.45+0.125+0.3},\ Attention\ \frac{0.125}{0.45+0.125+0.3},\ Critical\ \frac{0.3}{0.45+0.125+0.3}$$

$$RV = 2\ \times\ \frac{0.45}{0.45+0.125+0.3} + 3\ \times\ \frac{0.125}{0.45+0.125+0.3} + 4\ \times\ \frac{0.3}{0.45+0.125+0.3}\ = 2.822$$

**Starboard Crane Bearing**

10% decrement:

$$Normal\ \frac{0.1}{0.1+0.1+0.7},\ Caution\ \frac{0.1}{0.1+0.1+0.7},\ Critical\ \frac{0.7}{0.1+0.1+0.7}$$

$$RV = 1\ \times\ \frac{0.1}{0.1+0.1+0.7} + 2\ \times\ \frac{0.1}{0.1+0.1+0.7} + 4\ \times\ \frac{0.7}{0.1+0.1+0.7}\ = 3.441$$

20% decrement:

RV = (1 x 0.1) + (2 x 0.2) + (4 x 0.7) = 3.3

30% decrement:

RV = (2 x 0.3) + (4 x 0.7) = 3.4

**Port Crane Gearbox**

10% decrement:

$Normal\ \frac{0.667}{0.667+0.1},\ Critical\ \frac{0.1}{0.667+0.1}$

$RV = 1\ \times\ \frac{0.667}{0.667+0.1} + 4\ \times\ \frac{0.1}{0.667+0.1}$ = 1.389

20% decrement:

$Normal\ \frac{0.667}{0.667+0.2},\ Critical\ \frac{0.2}{0.667+0.2}$

$RV = 1\ \times\ \frac{0.667}{0.667+0.2} + 4\ \times\ \frac{0.2}{0.667+0.2}$ = 1.689

30% decrement:

$Normal\ \frac{0.667}{0.667+0.3},\ Critical\ \frac{0.3}{0.667+0.3}$

$RV = 1\ \times\ \frac{0.667}{0.667+0.3} + 4\ \times\ \frac{0.3}{0.667+0.3}$ = 1.929

**Starboard Crane Gearbox**

10% decrement:

$Caution\ \frac{0.775}{0.775+0.1},\ Critical\ \frac{0.1}{0.775+0.1}$

$RV = 2\ \times\ \frac{0.775}{0.775+0.1} + 4\ \times\ \frac{0.1}{0.775+0.1}$ = 2.226

20% decrement:

$Caution\ \frac{0.675}{0.675+0.2},\ Critical\ \frac{0.2}{0.675+0.2}$

$RV = 2\ \times\ \frac{0.675}{0.675+0.2} + 4\ \times\ \frac{0.2}{0.675+0.2}$ = 2.454

30% decrement:

$Caution\ \frac{0.575}{0.575+0.3},\ Critical\ \frac{0.3}{0.575+0.3}$

$RV = 2\ \times\ \frac{0.575}{0.575+0.3} + 4\ \times\ \frac{0.3}{0.575+0.3}$ = 2.682

## **Appendix 6 -** Research Questionnaires

Dear Sir/Madam,

A PhD research at Liverpool Logistics, Offshore and Marine (LOOM) Research Institute is currently being carried out on "Development of an efficient planned maintenance framework for marine and offshore machinery operating under highly uncertain environment". Recently, this subject has become a hot topic in the marine and offshore community due to a sudden shift in perception and thinking about maintenance of machinery used in marine and offshore operations.

The aim of the above research title is to generate a risk-based and decision-based methodology capable of delivering a maintenance framework for improvement and management of marine and offshore machinery systems' operation under highly uncertainty. In light of the above, a specific model is developed in order to achieve the aforementioned aim. A requirement for this study is to employ experts' judgement in determining the weights of each parameter of the model in order to prioritise them for an advanced computational analysis.

Thus, this study set out to provide an organised method for collecting experts' opinions in order to design a flexible yet robust planned maintenance system that can lead to the enhancement of safety and sustainability of the marine and offshore machinery and transportation systems.

In order to improve the quality and relevance of the research, the researcher would greatly appreciate your views by completing the following questionnaire and return using the email address given below. Please note that the completion of this questionnaire is voluntary and it will takes about 10 to 15 minutes of your time; however, your feedback will greatly enhance the research development and contribute to the industry wise opinion. Finally, the information provided and your identity will be treated with confidentiality. For further questions or enquiries about the study, please do not hesitate to contact the researcher.

Thank you.

Yours sincerely,

**Maurice Asuquo**

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## Questionnaire for Chapter 3

### Introduction

The primary goal of this study is to select the most significant events that contribute to the disruption of machinery operations in marine and offshore. The criteria and sub-criteria listed in Table 1 are the parameters that need to be investigated and evaluated using "*pair-wise comparison*" techniques.

Table 1: List of Criteria and sub-criteria

| Criteria | Sub-Criteria |
|---|---|
| Crane bearing<br>Crane clutch<br>Crane gearbox<br>Crane pump | Trend Analysis<br>Family Analysis<br>Environmental Analysis<br>Human Reliability Analysis<br>Design Analysis |

*Trend analysis is an aspect of technical analysis that tries to predict the future performance of machinery based on past data recorded. It is based on the idea that what has happened in the past gives an idea of what will happen in the future.*

*Family Analysis compares the uncertainties levels of group of similar or identical machinery to identify what is a usual or typical pattern.*

*Environmental Analysis evaluates the environmental conditions under which the machinery is currently operating.*

*Human Reliability Analysis will assess the operator's performance and competency during the machinery operations practice.*

*Design Analysis will assess the physical behaviour of the machinery or its component as specified by the manufacturer. It is used to predict the physical behaviour of just about any part or assembly under any loading conditions.*

To proceed with the "*pair-wise comparison*" technique, an expert needs to have a good knowledge of the qualitative descriptors or linguistic scales used for measurement in this study as represented in Tables 2(a) and (b). The tables describe the numerical assessment together with the linguistic meaning of each number. 2(a) explains the "Important" while the 2 (b) describes "Unimportant"

**Table 2(a):** Ratio scale for pair-wise comparison - Important

| Numbers | Strength of importance in Linguistic scales or qualitative descriptors |
|---|---|
| 1 | Equally Important |
| 3 | Weakly Important |
| 5 | Strongly Important |
| 7 | Very strongly important |
| 9 | Absolutely Important |
| 2,4,6,8 | Intermediate value of Important |

**Table 2(a):** Ratio scale for pair-wise comparison - Unimportant

| Numbers | Strength of importance in Linguistic scales or qualitative descriptors |
|---|---|
| 1 | Equally Unimportant |
| $^1/_3$ | Weakly Unimportant |
| $^1/_5$ | Strongly Unimportant |
| $^1/_7$ | Very strongly Unimportant |
| $^1/_9$ | Absolutely Unimportant |
| $^1/_2\,^1/_4\,^1/_6\,^1/_8$ | Intermediate value of Unimportant |

with reference to Table 2, an expert is required to give a possible judgement to all question based on his/her experience and expertise in the machinery operations. The judgement process has to be focus on how to achieve the goal of each section. To do so, please you are required to tick (⁄) as the rate of importance or priority of each criteria and sub-criteria in the given column. For instance:

**Goal: To select the most important component of computer**

### 1. Monitor Screen Device

| | Unimportant | | | | | | | | Equally Important | Important | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\frac{1}{9}$ | $\frac{1}{8}$ | $\frac{1}{7}$ | $\frac{1}{6}$ | $\frac{1}{5}$ | $\frac{1}{4}$ | $\frac{1}{3}$ | $\frac{1}{2}$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| To achieve the above goal, how important is the monitor screen compares to the mouse? | | | | | | | | | | | | | | | | / | |
| To achieve the above goal, how important is the monitor screen compares to the keyboard? | | | | | | | | | | | | / | | | | | |
| To achieve the above goal, how important is the monitor screen compares to the CPU? | | | / | | | | | | | | | | | | | | |

## Explanation:

- The monitor screen is 8 times more “important” than the mouse. It is because we can still use our computer even without the mouse. If the mouse is broken, then we can use the short cut system to access any file or document in the computer, by using a keyboard for instance to print (Ctrl+P), to save document (Ctrl+S), etc.
- The monitor screen is 4 times more “Important” than the keyboard. It is because we can still explore a computer even without the keyboard. For instance, to search a

document in a file, we can use our mouse. We can also read journals or article papers on the monitor screen even without the keyboard. The only thing we cannot do without the keyboard is typing.

- The monitor screen is 1/7 times less "Important" than the CPU. The monitor is useless without the CPU.

**How to complete the questionnaire**

This questionnaire aims to compare nine criteria that are perceived in the condition monitoring of marine and offshore machinery in order of importance by employing Analytic Hierarchy Process (AHP) to determine their priority ranking for decision-making.

The questionnaire is divided into two parts 1 and 2. Part 1 has the nine criteria which consist of group A (Ship crane's components), and group B (Ship crane's component/criteria). An example is given illustrating how the questionnaires should be filled. Part 2 consist of two questions; one on expert's experiences and the second on academic qualifications.

**<u>Example</u>**

Part 1: Group A: If you think the first criterion **Crane Bearing** is strongly important in condition monitoring of the ship crane than the second criterion **Crane Clutch**, then please tick as follows:

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Criterion | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | Criterion |
| Crane bearing | | | | | X | | | | | | | | | | | | | Crane clutch |

Alternatively, if the second criterion **Crane clutch** is strongly important in condition monitoring of the ship crane than the first criterion **Crane bearing**, then please tick as follows:

| | Scale of relative importance | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Criterion | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | Criterion |
| Crane bearing | | | | | | | | | | | | | X | | | | | Crane clutch |

*NB: Please remember to **<u>mark only one number on either the left or right side</u>** of the scale of importance or just the middle of the scale, which is equal importance.*

## Questionnaire

***"I have read the information sheet provided and I am happy to participate. I understand that by completing and returning this questionnaire I am consenting to be part of this research study and for my data to be used as described in the information sheet provided"***

### PART 1

| Group A: Crane Components | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scale of relative importance | | | | | | | | | | | | | | | | | |
| Criterion | Absolute **(9)** | Intermediate **(8)** | Very strong **(7)** | Intermediate **(6)** | Strong **(5)** | Intermediate **(4)** | Weak **(3)** | Intermediate **(2)** | Equal **(1)** | Intermediate **(2)** | Weak **(3)** | Intermediate **(4)** | Strong **(5)** | Intermediate **(6)** | Very strong **(7)** | Intermediate **(8)** | Absolute **(9)** | Criterion |
| bearing | | | | | | | | | | | | | | | | | | clutch |
| bearing | | | | | | | | | | | | | | | | | | gear |
| bearing | | | | | | | | | | | | | | | | | | pump |
| clutch | | | | | | | | | | | | | | | | | | gear |
| clutch | | | | | | | | | | | | | | | | | | pump |
| gear | | | | | | | | | | | | | | | | | | pump |

| Group B: Crane Bearing | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scale of relative importance | | | | | | | | | | | | | | | | | |
| Criterion | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | Criterion |
| Trend Analysis | | | | | | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | | | | | | Design Analysis |

| Group B: Crane Clutch | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scale of relative importance | | | | | | | | | | | | | | | | | |
| Criterion | Absolute (9) | Intermediate (8) | Very strong (7) | Intermediate (6) | Strong (5) | Intermediate (4) | Weak (3) | Intermediate (2) | Equal (1) | Intermediate (2) | Weak (3) | Intermediate (4) | Strong (5) | Intermediate (6) | Very strong (7) | Intermediate (8) | Absolute (9) | Criterion |
| Trend Analysis | | | | | | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | | | | | | Design Analysis |

| Group B: Crane Gearbox | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scale of relative importance | | | | | | | | | | | | | | | | | |
| Criterion | Absolute (9) | Intermediate | Very strong (7) | Intermediate | Strong (5) | Intermediate | Weak (3) | Intermediate | Equal (1) | Intermediate | Weak (3) | Intermediate | Strong (5) | Intermediate | Very strong (7) | Intermediate | Absolute (9) | Criterion |
| Trend Analysis | | | | | | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | | | | | | Design Analysis |

| Group B: Crane Hydraulic Pump | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scale of relative importance | | | | | | | | | | | | | | | | | |
| Criterion | Absolute (9) | Intermediate | Very strong (7) | Intermediate | Strong (5) | Intermediate | Weak (3) | Intermediate | Equal (1) | Intermediate | Weak (3) | Intermediate | Strong (5) | Intermediate | Very strong (7) | Intermediate | Absolute (9) | Criterion |
| Trend Analysis | | | | | | | | | | | | | | | | | | Family Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Trend Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Environmental Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Family Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Human Reliability Analysis |
| Environmental Analysis | | | | | | | | | | | | | | | | | | Design Analysis |
| Human Reliability Analysis | | | | | | | | | | | | | | | | | | Design Analysis |

## PART 2

### Question 1

Choose from letter A-E, one that best describe your experience in the field of expertise (***please tick the appropriate box***).

(A) □ 1-5 years
(B) □ 6-10 years
(C) □ 11-30 years
(D) □ Over 30 years
(E) □ None of the above

### Question 2

Please give your industry position and highest academic qualification in the appropriate box.

Industry position

| |
|---|
| |

Highest academic qualification

| |
|---|
| |

## Questionnaire for Chapter 5

### Introduction

The primary goal of this study is to select the most appropriate maintenance strategy to optimise the operational efficiency of marine and offshore machinery under an uncertain environment. The decision alternatives and evaluation criteria listed in Table 1 are the parameters that need to be considered and evaluated using "*fuzzy Linguistic variables scale*" techniques.

**Table 1:** List of Decision Alternatives and Evaluation Criteria

| Decision Alternatives | Evaluation Criteria |
|---|---|
| Run-to-failure maintenance<br>Preventive maintenance<br>Condition based maintenance<br>Reliability centred maintenance | Equipment reliability<br>Equipment cost<br>Equipment safety<br>Equipment availability<br>Equipment downtime |

*Equipment reliability is perceived as the probability that an equipment system will operate at a specified performance level for a specific period.*

*Equipment cost includes equipment capital cost, cost due to unplanned downtime of equipment, labour cost, and cost involved with repair or replacement of equipment*

*Equipment safety is the condition of equipment being protected from or being unlikely to cause danger, risk, or injury during operation.*

*Equipment availability can be defined as the degree to which the machine / equipment in context is in a specified operable and committable state at the start of operation, when the operation is called for at an unknown (i.e. a random) time.*

*A period during which an* ***equipment*** *or* ***machine*** *is not functional or cannot work is referred to as the equipment downtime.*

To proceed with the "*fuzzy Linguistic variables scale*" technique, an expert needs to have a good knowledge of the linguistic variables and their corresponding trapezoidal fuzzy scales used for measurement in this study as represented in Tables 2. The tables describe the numerical assessment together with the linguistic meaning of each variable.

**Table 2**: Fuzzy Linguistic Variables and Corresponding Trapezoidal Scales

| **Linguistic Variables** | **Corresponding Scale** |
|---|---|
| Very Low | (0, 0, 0.1, 0.2) |
| Low | (0.1, 0.25, 0.25, 0.4) |
| Medium | (0.3, 0.5, 0.5, 0.7) |
| High | (0.6, 0.75, 0.75, 0.9) |
| Very High | (0.8, 0.9, 1, 1) |

with reference to Table 2, an expert is required to give a possible judgement to all question based on his/her experience and expertise in the machinery maintenance. The judgement process has to be focus on how to achieve the goal of each decision alternative with respect to the evaluation criteria. To do so, please you are required to enter one out of the five linguistic variables against each of the decision alternatives with respect to the evaluation criteria in the given column. For instance, see Table 3.

**Table 3:** Example

| **EVALUATION CRITERIA** | **DECISION ALTERNATIVES** | | | |
|---|---|---|---|---|
| | Run-To-Failure Maintenance | Preventive Maintenance | Condition Based Maintenance | Reliability Centred Maintenance |
| Reliability | VH | | | |
| Cost | VL | | | |
| Safety | M | | | |
| Availability | L | | | |
| Downtime | H | | | |

**Explanation:**

- VH = Very High, VL = Very Low, M = Medium, L = Low, H = High.
- From the second column, row 3; with run-to-failure maintenance, reliability of the equipment is considered to be Very High.
- From the second column, row 4; with run-to-failure maintenance, cost associated with the equipment maintenance is considered to be Very Low.
- From the second column, row 5; with run-to-failure maintenance, equipment safety is considered to be Medium.
- From the second column, row 6; with run-to-failure maintenance, equipment availability is considered to be Low.
- From the second column, row 7; with run-to-failure maintenance, equipment downtime is considered to be High.

## Questionnaire

***"I have read the information sheet provided and I am happy to participate. I understand that by completing and returning this questionnaire I am consenting to be part of this research study and for my data to be used as described in the information sheet provided"***

### How to complete the questionnaire

This questionnaire is divided into two sections A and B. Section A is using the fuzzy linguistic variables to determine decision alternation based on the evaluation criteria. While Section B is about the expert's experiences and academic qualifications.

Now, please complete the two sections of the questionnaire as instructed.

### Section A

Use the five linguistics variables VL, L, M, H, and VH to fill in the empty cells corresponding to each of the decision alternative and the evaluation criteria.

| **EVALUATION CRITERIA** | **DECISION ALTERNATIVES** | | | |
|---|---|---|---|---|
| | Run-To-Failure Maintenance | Preventive Maintenance | Condition Based Maintenance | Reliability Centred Maintenance |
| Reliability | | | | |
| Cost | | | | |
| Safety | | | | |
| Availability | | | | |
| Downtime | | | | |

### Section B

### Question 1

Choose from letter A-E, one that best describe your experience in the field of expertise (***please tick the appropriate box***).

(F) □ 1-5 years

(G) □ 6-10 years

(H) □ 11-25 years

(I) □ Over 25 years

(J) □ None of the above

**Question 2**

Please give your industry position and highest academic qualification in the appropriate box.

Industry position

| |
|---|
| |

Highest academic qualification

| |
|---|
| |